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Digital Competences of Romanian High-School Graduates: An Analysis of Residence, Gender, and Track Gaps in the 2025 Baccalaureate Data, Mirrored against the BRIO–UNICEF National Digital Literacy Assessment

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A R T I C L E I N F O

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A B S T R A C T

Digital competence is declared a key competence of European education, yet its direct measurement, on large populations and with objective data, remains rare in the Romanian context. This paper draws on two independent and complementary sources of real data: the scores on the digital competences test within the 2025 Baccalaureate examination (first session), for 94,861 candidates with a valid score, and the results of the national digital literacy assessment conducted by BRIO at the initiative of UNICEF on a sample of 14,847 students. The objective of the study is to quantify the gaps in digital competence by area of residence, gender, and study track and profile, as well as to verify the relationship between digital competence and general school performance. The national mean score on the digital test was 48.9 points (SD = 23.3), with a nearly symmetrical distribution. The analysis revealed a significant and consistent rural–urban gap: urban candidates scored, on average, 51.6 points, against 44.7 in rural areas, a difference of nearly 7 points ($t = 45.3$; $p < 0.001$; $d = 0.30$), directionally confirmed by the BRIO assessment (a 4-percentile-point gap across the entire school population). The strongest differentiating factor, however, was the study track and profile: graduates of the sciences profile scored, on average, 62.0 points, against 30.3 for the sports profile, and the theoretical track exceeded the technological one by 14 points. A multiple regression model explained 16.2% of the variance in the digital score, with study profile and computer-science specialisation being the strongest predictors, followed by area of residence. Digital competence correlated positively with the overall Baccalaureate average ($r = 0.41$). The central conclusion is that the digital gap among Romanian graduates is structured primarily by the chosen educational track and, secondarily but consistently, by area of residence, pointing to the need for interventions both at the level of tracks with low digital competence and at the rural territorial level.

1. Introduction

1.1. The context of digital competence as an educational outcome

Digital competence has figured, for over a decade, among the eight key competences for lifelong learning defined at the European level, and the European Digital Competence Framework (DigComp), in its successive versions, has given it a detailed operational structure, articulated around domains such as information literacy, communication and collaboration, digital content creation, safety, and problem-solving. This declarative centrality has not, however, been matched, in the Romanian context, by a systematic and comparable measurement of the actual level of digital competence attained by students at the end of their schooling (Fraillon, J., et all, 2019).

The absence of measurement has a direct consequence for educational policy: in the absence of objective data on who exactly has low digital competences and in what context, remedial interventions remain generic, addressed to "students" in general, instead of being targeted at the effectively disadvantaged groups. The identification of these groups, by area of residence, by track, by profile, is the precondition of any rational allocation of training and equipment resources (Iliescu, D., 2022. Cohen, J., 1988)).

The stakes of this identification have risen with the acceleration of the digitalisation of the economy and of social life (Carretero, S., et all, 2017). Digital competence has ceased to be a specialised skill, useful only in certain occupations, and has become a condition of participation in economic, civic, and educational life. A graduate with low digital competences is not only disadvantaged in the labour market, but also more exposed

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to disinformation, less able to access digitalised public services, and more vulnerable to the risks of the online environment (Vuorikari, R., et al, 2022). From this perspective, the gaps in digital competence identified in this study are not mere differences in school performance, but potential lines of social fracture with lasting consequences (Lukacs, E. et all, 2012).

This paper responds to this need by drawing on an insufficiently exploited fact: the digital competences assessment within the Baccalaureate examination produces, annually, a standardised measurement of digital competence for the entire population of high-school graduates, and since 2025 these data have been published in open format. This is one of the largest databases of directly measured digital competence available in Romania, a system-level diagnostic instrument, used so far predominantly administratively rather than analytically.

1.2. Two complementary sources of real data

The study rests on two independent sources. The first is the open dataset of the 2025 Baccalaureate, first session, published by the Ministry of Education, which contains, for each candidate, the score obtained on the digital competences test (a value between 0 and 100), together with area of residence, gender, track, profile, specialisation, and the overall examination result. The second is the National Report on the Digital Literacy Level of Students in Romania, produced by BRIO at the initiative of UNICEF and published in 2026, a standardised assessment of a representative sample of 14,847 students across the whole of pre-university education.

The two sources complement each other in a methodologically valuable way. The Baccalaureate data cover the entire population of graduates, not a sample, but only for a single age cohort (twelfth-grade students) and through a single test. The BRIO assessment covers a sample, but one representative of all age levels, with an instrument built explicitly on the DigComp framework and psychometrically validated. The convergence of the findings of the two sources, where it appears, considerably strengthens confidence in the conclusions, since it derives from different instruments and populations.

1.3. Objectives and research questions

The general objective of the study is to describe and explain the variation in the digital competence of Romanian high-school graduates. The specific research questions are: (a) What is the mean level and the distribution of digital competence nationally? (b) Is there a gap in digital competence between rural and urban areas, and if so, how large is it? (c) Are there differences by gender? (d) How much do track, profile, and study specialisation differentiate digital competence? (e) What is the relationship between digital competence and general school performance? (f) To what extent do the findings from the Baccalaureate data converge with those of the BRIO national assessment?

2. Conceptual framework and literature

2.1. The concept of digital competence and the DigComp framework

Digital competence has evolved conceptually from a narrow sense, equivalent to computer-operation skills, to a broad one, which includes the capacity to use digital technologies critically, creatively, safely, and responsibly, across a diversity of life contexts. The European Digital Competence Framework for Citizens (DigComp), developed by the Joint Research Centre of the European Commission, has become the dominant reference in operationalising this broad sense. In its successive versions, DigComp structures digital competence around five domains: information and data literacy; communication and collaboration; digital content creation; safety; and problem-solving.

This domain structure has an important methodological consequence: digital competence is not a unidimensional construct, but a set of partially independent facets. A student may be advanced in the use of communication applications, but a beginner in the critical evaluation of information or in the protection of personal data. Measurement instruments differ precisely in the weight they assign to each domain, which explains why two assessments of the same population may produce slightly divergent results, an observation relevant to the triangulation of the two sources in the present study.

2.2. The digital divide: from access to competence

International research on the digital divide has, in turn, gone through an evolution in three stages, synthesised in the specialist literature. The "first-level divide" referred to physical access to technology and has been largely overcome in developed countries. The "second-level divide" concerns skills and patterns of use: at equal access, individuals use technology with differing effectiveness. The "third-level divide" concerns the capacity to translate use into concrete outcomes, educational, professional, social.

The digital competence measured at the Baccalaureate is situated, conceptually, at the level of the second divide, that of skills, since it assesses the actual capacity to operate with digital instruments, not the mere existence of access (Pricopoaia, O., et all, 2024). The Impact of Artificial Intelligence on Environmental Challenges Embedded in Macromarketing Strategies. *Review of International Comparative Management/Revista de Management Comparat International*, *25*(5), 819. Studies that have analysed the determinants of these skills consistently identify a set of factors: the socio-economic level of the family, the area of residence, the type of school, and exposure to formal instruction. The present study tests, on Romanian data, precisely this structure of factors, to the extent that they are observable in the available open data.

2.3. Measuring digital competence in Romania: earlier studies

In the Romanian context, the systematic measurement of students' digital competence is recent. Beginning in 2022, BRIO conducted a series of standardised assessments aligned with the DigComp framework, initially of a predominantly explanatory character, focused on identifying the factors associated with the level of digital competences, such as family background, access to technology, and attitudes. The 2026 study, used as a benchmark in the present paper, differs through its character as a system-level diagnostic assessment, on a much larger and representative sample.

At the comparative international level, the ICILS study (International Computer and Information Literacy Study), conducted by the IEA, provides the reference methodological framework for assessing students' digital competence on nationally representative samples. Its findings, a modest general level, persistent socio-economic gaps, uneven progression over the course of schooling, offer an international context against which the Romanian results can be interpreted. The specific contribution of the present study within this landscape is the use of a census-type data source, the Baccalaureate test, which covers the entire population of graduates, not a sample, which eliminates, for the studied cohort, any sampling uncertainty (Scheerder, A., et all, 2017).

3. Data and methods

3.1. Data sources

The primary source of analysis was the open dataset of the 2025 Baccalaureate examination, first session, published by the Ministry of Education on 1 October 2025. The file contains 107,961 individual records, one for each enrolled candidate. Of these, 94,861 have a valid score on the digital competences test, which constitutes the analysis sample of the present study. The difference is accounted for by candidates who did not sit the test or for whom the score was not recorded.

The secondary source, used as a validation benchmark, was the BRIO–UNICEF National Report on digital literacy (2026), from which the relevant aggregate results were drawn: median and mean scores by area of residence, by gender, and by performance category. Being a published report, only aggregate statistics, not individual data, were extracted from it.

It is important to note that the two instruments measure digital competence in different ways and on different scales. The Baccalaureate test produces a percentage score (0–100) based on a standardised practical and theoretical assessment. The BRIO assessment produces percentile-type scores, of a diagnostic character, combining knowledge, behavioural, and self-assessment items. For this reason, the comparison between the two sources is directional, of the direction and the relative magnitude of the gaps, not a direct comparison of absolute values.

3.2. Variables

The main dependent variable was the score on the digital competences test (0–100). This test, a compulsory component of the Baccalaureate examination, assesses candidates' digital competences through a combination of practical tasks and theoretical items, aligned with the domains of the digital competence framework. The result is expressed through a score which, although it does not enter into the calculation of the general pass average, is recorded on the Baccalaureate diploma and certifies the graduate's level of digital competence. For this reason, the test offers a standardised, compulsory, and high-stakes measure of digital competence for the entire population of graduates.

The independent and classification variables were: the candidate's area of residence (urban / rural), gender (female / male), track (theoretical / technological / vocational), study profile (sciences, humanities, technical, services, natural resources, pedagogical, artistic, theological, sports), and an indicator of specialisations with an intensive computer-science profile (mathematics–computer science, computer-technology operator technician, automation technician, telecommunications technician). The overall Baccalaureate average and pass status were used as correlated outcome variables.

An additional variable examined was the form of education. The analysis showed that graduates from day education (97.4% of the sample) scored, on average, 49.3, considerably higher than those from evening (32.8) and reduced-frequency (32.7) education. Since the latter forms largely comprise candidates from earlier cohorts and atypical populations, the main analyses of the study focus on the whole sample, but this difference is flagged as a relevant contextual factor.

3.3. Analysis strategy

The analysis followed a four-stage sequence. The first consisted in describing the general distribution of the score and in classifying candidates into four competence categories, according to the usual thresholds of the digital competences certificate: beginner (0–24), intermediate (25–49), advanced (50–74), and experienced (75–100). The second stage compared scores across groups, residence, gender, track, through t-tests, analysis of variance, and effect sizes (Cohen's d, eta squared). The third stage built a multiple linear regression model to estimate the independent contribution of each factor. The fourth examined the relationship between digital competence and general performance, through correlation and through comparing scores between passing and failing candidates. The significance threshold was set at 0.05; given the large sample size, the interpretive emphasis was placed on effect sizes, not on statistical significance alone.

4. Results

4.1. The level and general distribution of digital competence

The national mean score on the digital competences test was 48.9 points (SD = 23.3), with a median of 48 and a skewness coefficient close to zero (0.10), indicating a nearly symmetrical distribution, spread across almost the entire scale. This mean value, situated below the midpoint of the scale, confirms at the level of the entire population of graduates the central finding of the BRIO assessment, a modest general level of functional digital competence. It should be recalled that the BRIO median score, expressed in percentiles, was 44, a comparable value in relative positioning.

The distribution of the score, visible in the figures that follow, presents a slightly multimodal structure, with concentrations around the values of 33, 57, and 76 points. This multimodality is not a statistical artefact but reflects, most probably, the superposition of subpopulations with differing levels of digital instruction, an early indication of the heterogeneity that the analyses by track and profile will confirm. A homogeneous population would produce a unimodal distribution; the presence of several peaks suggests, on the contrary, the existence of distinct competence groups within the same cohort.

The breakdown by category nuances the mean. More than half of the candidates (51.9%) fall into the beginner and intermediate categories, that is, below the 50-point threshold, while only one in five (19.6%) reaches the experienced level. This concentration in the lower-median zone of the scale is consistent with the BRIO observation that approximately 70% of students are in categories indicating risk or limited functionality, even if the thresholds of the two instruments are not identical.

Table 1. Distribution of candidates by digital competence category (2025 Baccalaureate, first session)

Competence category	Score range	No. of candidates	Share (%)
Beginner	0–24	15,874	16.7
Intermediate	25–49	33,434	35.2
Advanced	50–74	26,961	28.4
Experienced	75–100	18,592	19.6
Total	0–100	94,861	100.0

Table 2 summarises the descriptive statistics of the digital score across the main analysis groups, offering an overview of the structure of the data before the formal testing of differences.

Table 2. Descriptive statistics of the digital competences score, by analysis group

Group	No. of candidates	Mean	SD	Median
National total	94,861	48.9	23.3	48
Urban	57,995	51.6	23.1	52
Rural	36,866	44.7	22.9	42
Female	48,893	47.3	22.7	45
Male	45,968	50.6	23.7	50
Theoretical track	51,742	54.8	22.8	56
Technological track	31,668	40.8	21.3	38
Vocational track	11,451	44.8	22.9	43

4.2. The rural–urban gap

The comparison of scores by area of residence revealed a significant gap. Urban candidates (n = 57,995) scored a mean of 51.6 (SD = 23.1), while rural candidates (n = 36,866) scored a mean of 44.7 (SD = 22.9). The difference of 6.9 points is highly statistically significant (t = 45.3; $p < 0.001$) and corresponds to an effect size of small-to-medium magnitude (d = 0.30).

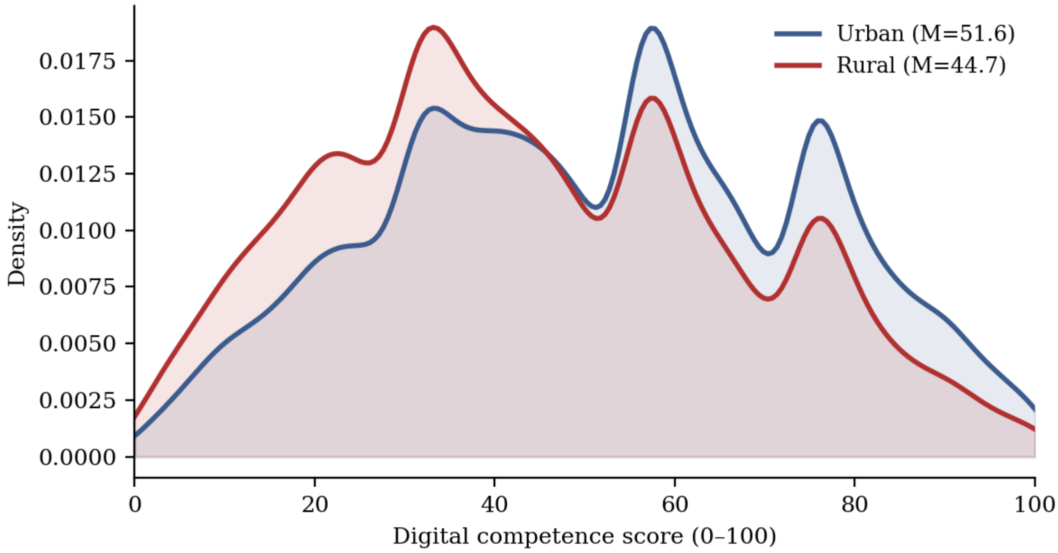

Figure 1. Density distribution of the digital competences score, by area of residence (2025 Baccalaureate)

Figure 1 shows that the gap is not merely a difference of means, but a shift of the entire distribution. The rural curve has its maximum density concentrated around the value of 33 points, while the urban curve presents more pronounced peaks in the upper zone, around the values of 57 and 76 points. In other words, the urban environment not only has a higher mean, but proportionally produces more candidates with high digital competence.

This finding directionally converges with the BRIO national assessment, which reported a median score of 45.0 in urban areas against 41.0 in rural areas, a gap of 4.0 percentile points. The fact that two different instruments, on different populations (the entire graduate cohort versus a representative sample across all ages), produce the same direction and a comparable magnitude of the gap **considerably strengthens** the conclusion that the rural–urban gap in digital competence is real and structural, not an artefact of a particular measurement instrument.

The breakdown by competence category deepens the picture. In rural areas, 21.5% of candidates are in the beginner category, against 13.7% in urban areas; at the opposite pole, only 14.9% of rural candidates reach the experienced level, against 22.6% of urban ones. The chi-square test confirms the association between area of residence and competence category ($\chi^2 = 1863.9$; $p < 0.001$), with a modest but consistent strength of association (Cramér's V = 0.140).

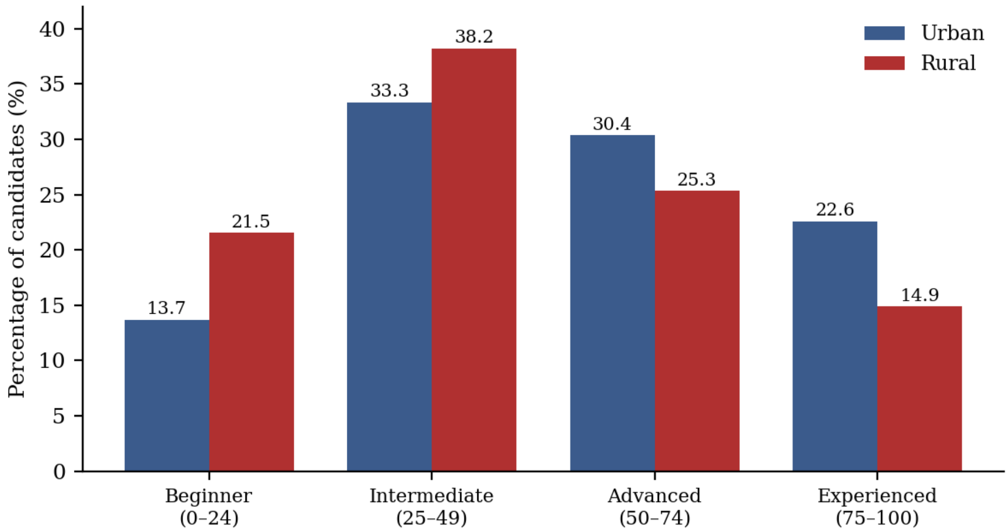

Figure 2. Distribution of candidates by digital competence category, compared by area of residence

A quantile analysis offers a finer picture of how the gap is distributed across the entire competence scale. Table 3 compares the two areas of residence at five points of the distribution. The gap is not uniform: it is most pronounced in the median zone of the distribution, 10 points at the median and at the upper quartile, and narrows at the extremes, to 5 points at the 10th and 90th percentiles.

Table 3. Digital competences score by percentile, compared by area of residence

Percentile	Urban	Rural	Gap (points)
10th percentile	20	15	5
Lower quartile (25)	34	27	7
Median (50)	52	42	10
Upper quartile (75)	70	60	10
90th percentile	82	77	5

This structure of the gap has an interpretation relevant to intervention. The fact that the difference is greatest at the middle of the distribution, rather than at its base, suggests that the problem does not reduce to a small group of rural students with very low competences, but concerns the median rural student, the typical rural candidate remains 10 points behind their urban counterpart. At the lower extreme, where both areas have students with serious difficulties, and at the upper one, where both produce high-achieving students, the gap attenuates. The higher coefficient of variation in rural areas (0.51 against 0.45 in urban) confirms, in addition, a somewhat greater heterogeneity of competence in rural areas.

4.3. Gender differences

The analysis by gender produced a result that deserves separate discussion, as it partly contradicts the BRIO assessment. At the Baccalaureate test, male candidates scored a slightly higher mean (50.6; SD = 23.7) than female candidates (47.3; SD = 22.7), a difference of 3.3 points, statistically significant ($t = -22.3$; $p < 0.001$), but of small magnitude ($d = -0.15$).

In the BRIO assessment, the direction of the difference was reversed: girls scored slightly higher medians than boys (44.0 against 43.0). This apparent contradiction has, most probably, an explanation rooted in the content of the instrument. The BRIO assessment combines knowledge items with self-assessment and behavioural items, whereas the Baccalaureate test is a practical assessment oriented towards the actual operation of digital instruments. The difference in direction suggests that the two instruments capture partly distinct facets of digital competence, and the gender gap, in both cases of small magnitude, does not constitute a major structural factor, a conclusion both sources support, beyond the difference in direction.

The combined analysis of gender and residence, through a factorial analysis of variance, confirmed that the two effects are additive, not interactive. Both the effect of residence ($F = 1975$; $p < 0.001$) and that of gender ($F = 428$; $p < 0.001$) were significant, but the interaction between them did not reach the significance threshold ($F = 1.68$; $p = 0.195$). This means that the rural–urban gap has approximately the same magnitude for girls and boys, and the gender difference is maintained in both areas. The mean scores across the four combinations, from 53.2 for urban boys to 43.4 for rural girls, order themselves predictably, without unexpected reversals or amplifications.

4.4. Differences by track and study profile

The strongest differentiating factor of digital competence was neither residence nor gender, but the educational track. The comparison by track revealed wide differences: the theoretical track scored a mean of 54.8, the vocational track 44.8, and the technological track only 40.8. The analysis of variance confirms the significance of these differences ($F = 4107$; $p < 0.001$), with an effect size (eta squared = 0.080) considerably larger than that of the rural–urban gap.

Table 4. Digital competences score by study track

Track	No. of candidates	Mean score	SD	Median
Theoretical	51,742	54.8	22.8	56
Vocational	11,451	44.8	22.9	43
Technological	31,668	40.8	21.3	38

At the level of profiles, the amplitude is even greater. Graduates of the sciences profile scored the highest mean (62.0), followed by the pedagogical profile (58.0), while at the opposite pole are the sports profile (30.3) and the natural-resources profile (37.6). The difference between the sciences and the sports profiles, of over 31 points, far exceeds any other gap identified in the study, including the rural–urban gap, nearly five times smaller. Table 5 presents the mean score for all nine study profiles.

Table 5. Digital competences score by study profile, in descending order

Study profile	No. of candidates	Mean score	SD
Sciences (Real)	26,205	62.0	21.9
Pedagogical	2,160	58.0	19.3
Humanities	25,537	47.4	21.3
Artistic	3,303	47.3	20.9
Theological	1,694	47.0	21.1
Services	15,552	42.2	21.0
Technical	11,059	40.2	21.9
Natural resources & environment	5,057	37.6	20.5
Physical education and sport	3,794	30.3	18.4

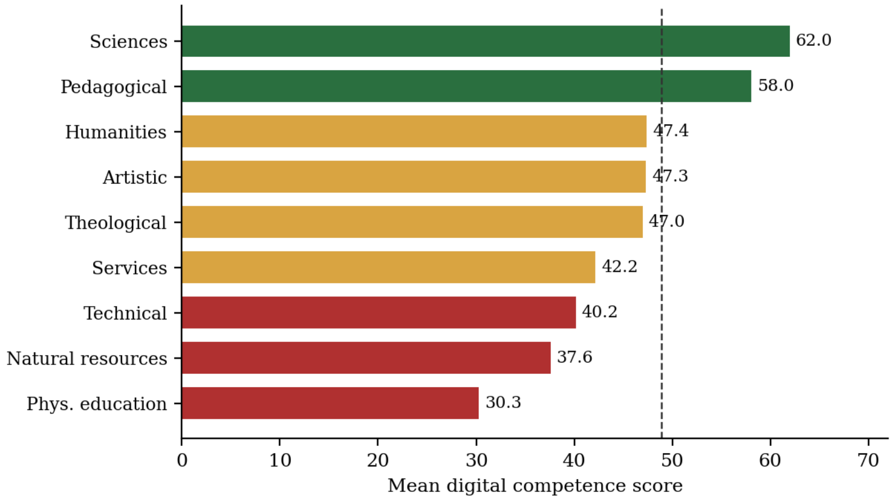

Figure 3. Mean digital competences score by study profile (the dashed line marks the national mean of 48.9)

Specialisations with an intensive computer-science profile, mathematics–computer science and the technical computing and telecommunications specialisations, scored a mean of 64.4, against 45.8 for the remaining specialisations, a difference of nearly 19 points. This result, although predictable, has an important confirmatory value: the Baccalaureate digital competences test effectively discriminates between students who followed an explicit digital-training path and the rest, which supports the content validity of the instrument.
The analysis at the level of individual specialisations, presented in Table 6, offers the finest picture of this stratification. The mathematics–computer science specialisation leads by a wide margin, with a mean score of 67.6, followed by the primary-teacher specialisation (60.8) and natural sciences (56.0). At the opposite pole, the sports-programme high school (30.3) and the technical maintenance and gastronomy specialisations (34–37) are situated more than 30 points below the top of the ranking.

Table 6. Digital competences score by main specialisation (over 1,000 candidates)

Specialisation	No. of candidates	Mean score	SD
Mathematics–computer science	13,538	67.6	20.7
Primary teacher–educator	1,484	60.8	18.5
Natural sciences	12,667	56.0	21.5
Plastic and decorative arts	1,184	48.5	20.6
Social sciences	9,284	48.0	21.7
Philology	16,253	47.0	21.0
Computer-technology operator technician	1,170	46.7	22.1
Technician in economic activities	6,891	44.8	21.1
Tourism technician	2,680	40.5	20.4
Gastronomy technician	1,349	36.6	20.4
Sports-programme high school	3,794	30.3	18.4

The second-place position of the primary-teacher specialisation deserves a note. It suggests that, beyond the explicit computer-science specialisations, high digital competence also appears in tracks with relatively high academic selection and with a pedagogical component that includes training in the use of educational technology. This reinforces the idea that the digital score reflects both specific computer-science instruction and the general academic level of the track.

The interaction between track and residence, shown in Figure 4, indicates that the rural–urban gap is maintained within each track, but does not cancel the gap between tracks. A theoretical-track graduate from a rural area (median 50.3) scores, on average, higher than a technological-track graduate from an urban area (median 42.8). In other words, the choice of track weighs more than the area of residence, although both matter.

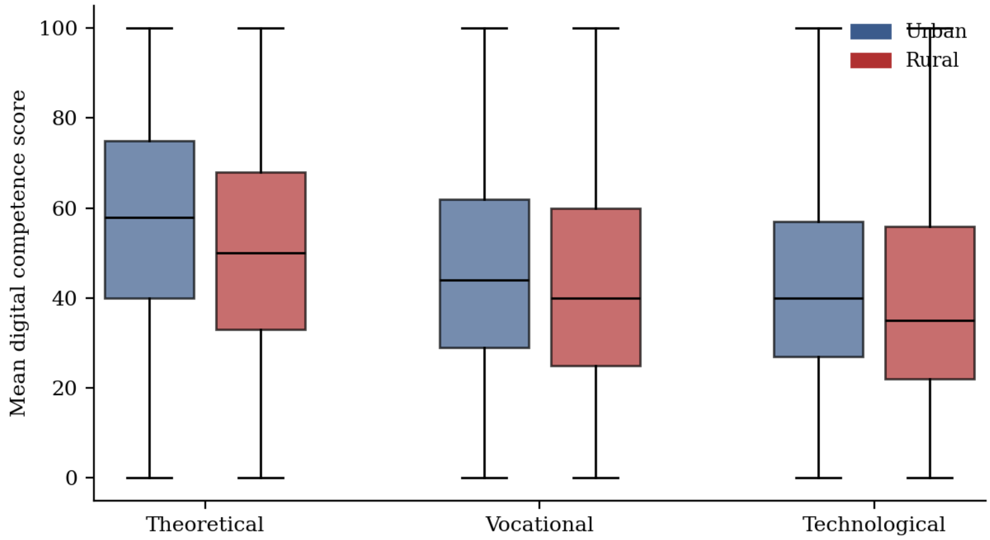

Figure 4. Distribution of the score by track and area of residence (box plots; extreme values omitted for legibility)

4.5. The distribution of competence categories across tracks

The breakdown by competence category within each track, presented in Table 7, shows how the mean gap translates into the structure of the population. In the theoretical track, over a quarter of graduates (26.9%) reach the experienced level, and only one in ten (10.6%) is at the beginner level. In the technological track, the ratio is almost completely reversed: only 9.4% reach the experienced level, while nearly a quarter (24.9%) remain at the beginner level.

Table 7. Distribution of digital competence categories within each track

Track	Beginner (%)	Intermediate (%)	Advanced (%)	Experienced (%)
Theoretical	10.6	30.6	31.8	26.9
Vocational	21.6	37.1	26.6	14.7
Technological	24.9	42.1	23.6	9.4

This reversal has a direct practical significance. The most numerous target group for a possible remedial intervention, graduates at the beginner level, is disproportionately concentrated in the technological and vocational tracks. A system-level intervention targeting these two tracks would therefore reach precisely the population with the greatest deficit, with a targeting efficiency superior to that of a generic intervention.

The composition of the extreme groups confirms and quantifies this concentration. Of the 18,592 candidates at the experienced level, 75.0% come from the theoretical track and 54.4% from the sciences profile, proportions far exceeding the shares of these categories in the total population (54.5% and 27.6% respectively). Over a third of experienced candidates (36.1%) come from a single specialisation, mathematics–computer science. At the opposite pole, of the 15,874 candidates at the beginner level, half (49.7%) come from the technological track and exactly half (50.0%) from rural areas, again, proportions clearly exceeding their general shares. The two extreme groups thus have almost opposite sociological profiles: the top is urban, theoretical, and computer-science-oriented; the bottom is rural and technological.

4.6. The multiple regression model

To estimate the independent contribution of each factor, a multiple linear regression model was built, with the digital score as the dependent variable and area of residence, gender, track, the sciences profile, and computer-science specialisation as predictors. The model explained 16.2% of the variance in the score (R^2 = 0.162; n = 94,861), a reasonable value for individual-level data, where the variation unexplained by observable factors is, by its nature, large.

Table 8. Multiple regression model for the digital competences score (R^2 = 0.162)

Predictor	b coef.	std. β	t	p
Urban residence	+4.62	0.097	32.2	<0.001
Female gender	−2.09	−0.045	−14.8	<0.001
Theoretical track	+7.02	0.150	38.6	<0.001
Vocational track	+4.12	0.058	17.6	<0.001
Sciences profile	+9.29	0.179	42.0	<0.001
Computer-science specialisation	+9.31	0.150	40.4	<0.001

The hierarchy of standardised coefficients confirms the conclusion of the bivariate analyses: the strongest predictors are the sciences profile (β = 0.18), followed equally by the theoretical track and computer-science specialisation (β = 0.15 each). Urban residence has an independent positive effect, but a smaller one (β = 0.10), and female gender a small negative effect (β = −0.05). The interpretation in natural units is direct: at the same track, profile, and gender, an urban candidate scores, on average, 4.6 points higher than a rural one, a gap that persists even after controlling for the educational track and that therefore measures the residence component proper of the inequality.

4.7. The relationship with general school performance

Digital competence correlated positively and moderately with the overall Baccalaureate average (r = 0.41; $p < 0.001$; n = 72,165), a relationship shown in Figure 5. Passing candidates scored a mean digital score of 54.0, against 36.3 for failing candidates, a difference of nearly 18 points.

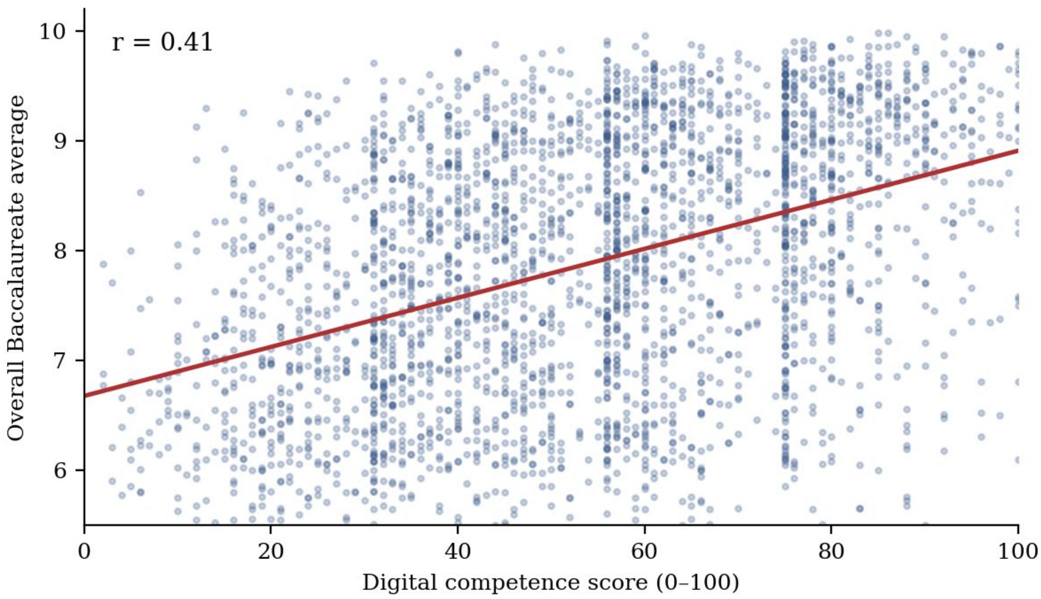

Figure 5. The relationship between the digital competences score and the overall Baccalaureate average (random sample of 3,000 candidates)

This correlation should not be interpreted causally. It reflects, most probably, a common underlying factor, study profile and the general level of academic preparation simultaneously influence both digital competence and general results. The correlation nonetheless confirms that the digital score is not an isolated measure, but integrates coherently into the general picture of school performance, which supports, once again, the validity of the test as an assessment instrument.

A more transparent way to express this link is to examine the Baccalaureate pass rate by digital competence category, shown in Figure 6. The gradient is pronounced and monotonic: of the candidates at the beginner level, only 41.7% passed the examination, while of those at the experienced level, 89.3% passed it. The pass rate thus rises by over 47 percentage points along the digital competence scale.

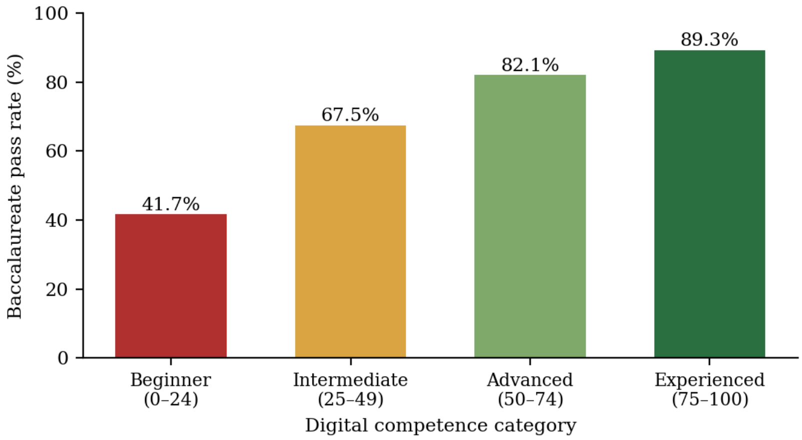

Figure 6. Baccalaureate pass rate by digital competence category

The gradient does not imply that the digital competences test causes passing, it does not, in fact, even enter into the calculation of the general average. It reflects, rather, the fact that the level of digital competence is a faithful indicator of the candidate's overall academic preparation: students who reach the end of high school with solid digital competences are, in general, the same ones who also have the preparation needed to pass the other tests. Digital competence functions, in this sense, as a marker of general school success, and its deficit signals a broader educational risk.

4.8. Synthesis of effect sizes

To allow the direct comparison of the magnitude of the various differentiating factors, Table 9 synthesises the effect sizes associated with each comparison. Their ordering confirms, at a single glance, the central conclusion of the study: the educational track produces the largest differences, followed by area of residence, while gender has the smallest effect.

Table 9. Synthesis of effect sizes for the main factors differentiating digital competence

Differentiating factor	Comparison	Difference of means	Effect size
Study profile	Sciences vs. sports	31.7 points	d ≈ 1.5 (very large)
Specialisation	Computer science vs. rest	18.6 points	d ≈ 0.8 (large)
Track	Theoretical vs. technological	14.0 points	η^2 = 0.080 (medium)
Residence	Urban vs. rural	6.9 points	d = 0.30 (small–medium)
Pass status	Passing vs. failing	17.7 points	d ≈ 0.8 (large)
Gender	Male vs. female	3.3 points	d = 0.15 (small)

4.9. Triangulation with the BRIO national assessment

The convergence between the two sources of real data can now be evaluated systematically. Table 10 sets side by side the equivalent findings of the Baccalaureate test and of the BRIO assessment, on the dimensions that both measures. It should be recalled that the absolute values are not directly comparable, the Baccalaureate test produces percentage scores, and BRIO percentile scores, so that the comparison concerns the direction and relative magnitude of the gaps, not the equality of the figures.

Table 10. Systematic comparison of the findings of the two data sources

Dimension	2025 Baccalaureate finding	BRIO 2026 finding	Convergence
General level	Mean 48.9/100; 52% below threshold	Median 44 percentiles; ~70% at risk	Yes, modest level
Rural–urban gap	Urban 51.6 vs rural 44.7 (7 pts)	Urban 45.0 vs rural 41.0 (4 pts)	Yes, same direction
Gender gap	Boys > girls (3.3 pts)	Girls > boys (1.0 pt)	Opposite direction, both small
Population	Entire graduate cohort	Representative sample, all ages	Complementary

The table reveals an informative pattern: the two sources converge strongly where the gap is structural, the modest general level and the rural disadvantage, and diverge where the difference is small and, plausibly, instrument-dependent, gender. This configuration is exactly the one that strengthens confidence in the conclusions: a gap that appears in the same direction in two different instruments, on two different populations, is almost certainly real; a difference that changes direction between instruments is, most probably, an artefact of the mode of measurement and should not guide public policy.

It is worth noting that the BRIO assessment brings, in addition to the Baccalaureate data, a finding that the latter cannot provide: the analysis by age showed a slow and uneven increase in digital competence with advancing age, without a clear jump between schooling cycles. This observation suggests that the development of digital competence is not systematically supported by the formal educational path, but depends largely on contexts external to school. The Baccalaureate data, limited to a single age cohort, cannot directly test this hypothesis, but their pattern, competence concentrated in tracks with explicit computer-science instruction, is fully coherent with it: where school teaches digital competences explicitly, results are better, which indirectly confirms that formal exposure matters.

The performance-category structure of the BRIO assessment, presented in Table 11, offers an additional benchmark. Nearly 37% of the students assessed by BRIO are in the risk categories (major or moderate), and over half in the limited-functionality category, a category which, according to the report, does not indicate an adequate functional level, but an intermediate zone of vulnerability. Only 8.5% reach good or high functionality. This distribution, strongly concentrated in the lower-median zone, is remarkably similar in shape to that of the Baccalaureate scores, where 51.9% of candidates are below the 50-point threshold.

Table 11. Distribution of students by performance category in the BRIO national assessment (n = 14,847)

BRIO category	Range (percentiles)	No. of students	Share (%)
Major risk	0–19	227	1.5
Moderate risk	20–39	5,208	35.1
Limited functionality	40–59	8,150	54.9
Good functionality	60–79	1,233	8.3
High functionality	80–100	29	0.2

5. Discussion

5.1. The educational track as the main differentiating factor

The central result of the study is the hierarchy of differentiating factors. Contrary to an intuitive assumption that would place area of residence at the centre of the digital gap, the data show that the dominant factor is the educational track, the track, profile, and specialisation. The difference between the sciences and the sports profiles (over 31 points) is nearly five times greater than the rural–urban gap (nearly 7 points).

This finding has an important interpretation. The digital competence measured at the Baccalaureate is not, in the main, a diffuse competence, acquired informally through mere exposure to technology, but one strongly linked to the content of formal training. Students from tracks and profiles with an explicit computer-science component, with hours of computer science and information technology in the common core or in the specialisation, score markedly higher. This suggests that formal instruction works, but that access to it is unequally distributed across educational tracks, and the choice of track at the age of 14–15 thus becomes a major determinant of digital competence at graduation.

5.2. The persistence of the rural–urban gap

The rural–urban gap, although secondary in magnitude to that between tracks, is remarkable for its consistency. It appears in the Baccalaureate data ($d = 0.30$), is directionally confirmed by the BRIO assessment (4 percentile points), and persists in the regression model even after controlling for track and profile ($\beta = 0.10$). This persistence after control is the most important piece of information: it shows that the rural–urban gap does not reduce entirely to the fact that rural students more frequently choose tracks with low digital competence, but contains a residual component of its own.

The residual component plausibly captures the contextual factors of the rural environment that the instrument does not measure directly: reduced access to devices and connections at home, a poorer offer of extracurricular digital activities, the difficulty of rural schools in attracting qualified computer-science teachers. The convergence with the BRIO assessment, which explicitly attributed the gap to “structural and educational-context factors, not individual differences in capacity,” reinforces this interpretation.

5.3. The methodological value of triangulation

A methodological contribution of the study is the demonstration of the value of triangulating two independent sources of real data. The Baccalaureate data offer population coverage and an objective score, but are limited to one age cohort and a single test. The BRIO assessment offers representativeness across all ages and an instrument validated on the DigComp framework, but on a sample. The fact that the two converge on the rural–urban gap and the modest general level, but diverge slightly on gender, offers a more nuanced picture than either could have offered separately: residence gaps are robust to the instrument, while the gender difference is sensitive to the mode of measurement.

5.4. Relation to the international context

The results fall within the pattern documented by the international research on students' digital competence. The ICILS study, conducted by the IEA on representative samples from numerous educational systems, consistently reports three findings that the Romanian data confirm: a general level of digital competence more modest than the rhetoric about "digital natives" suggests; persistent socio-economic and territorial gaps; and a weak link between the mere use of technology and the actual competence to use it productively. The modest level identified here, both in the Baccalaureate data and in the BRIO assessment, is therefore not a Romanian exception, but a local manifestation of an international pattern.

The Romanian specificity, in this comparative landscape, is less the general level, comparable to that of other systems with similar development, and more the extent of the differentiation across educational tracks. The fact that a sciences-profile graduate scores, on average, more than twice the score of a sports-profile graduate indicates a stratification of digital competence across tracks more accentuated than in systems with a stronger common core of digital competences (Iancu, D. E., & Iliescu, D., 2023). This observation places the problem less in the zone of the absolute level and more in that of the equity of distribution, which also orients the policy recommendations.

5.5. Digital competence as a marker of educational risk

The strong relationship between digital competence and the pass rate suggests a use of the test beyond its declared purpose. Since the digital score correlates with the whole of academic preparation and clearly separates candidates at risk of failure, it can function as an early-warning instrument. A student with low digital competence in the years before graduation is, according to this pattern, a student with a broader educational risk, who would benefit from a support intervention before the final examination (van Deursen, A. J. A. M., 2019).

This use has the advantage of availability: unlike composite indicators that are difficult to construct, the digital score is already measured and, since 2025, published. A monitoring system tracking the evolution of digital competence across successive cohorts would offer, at low cost, a map of educational risk by track, profile, and area of residence, updatable annually.

5.6. Implications for educational policy

Two directions of intervention follow from the results, corresponding to the two major factors identified. The first concerns the tracks and profiles with low digital competence, in particular the technological track and the sports, natural-resources, and services profiles. Since these bring together a large number of students (the technological track alone has over 31,000 candidates), a strengthening of the digital competences component in the common core of these tracks would have a significant system-level effect, addressing precisely the zone with the greatest deficit.

The second direction concerns rural areas, where the gap persists independently of the educational track. Here, the effective intervention is not one of curriculum, but one of infrastructure and human resources: equipping rural schools, ensuring connectivity, and, above all, attracting and retaining computer-science teachers. The two directions do not substitute for one another, but complement each other: the first reduces the gap between tracks, the second the gap between areas, and an effective programme for reducing digital inequality must pursue them simultaneously.

Finally, the results raise a question of curricular equity that the study can flag but not resolve. The fact that the choice of track at the age of 14–15 largely determines digital competence at graduation means that a decision taken at the beginning of adolescence, often under the influence of family and territorial factors, has lasting consequences for a competence declared essential for all citizens. If society considers digital competence a universal key competence, then its concentration in certain tracks becomes a matter of equity, which would justify ensuring a common minimum threshold of digital training across all tracks, regardless of profile.

6. Limitations and conclusions

6.1. Limitations of the research

The first limitation stems from the nature of the Baccalaureate test, which measures digital competence at a single point in time and through a specific instrument, whose component domains are not disaggregated in the open data. It cannot therefore be established whether the identified gaps are distributed uniformly across all domains of digital competence or concentrated in some of them.

The second limitation is the absence, in the open data, of the county or school-unit level, which prevents fine territorial analysis and multilevel modelling. The SIIIR codes of the units are present, but without a public correspondence table associating them with counties. Territorial analysis thus remains at the level of the rural–urban dichotomy, complemented by the county benchmarks from the BRIO report.

The third limitation is the cross-sectional and correlational nature of the data: the identified relationships are associations, not causal relationships. In particular, the correlation between digital competence and the general average cannot be interpreted as an effect of one on the other. The fourth limitation concerns the comparability of the two sources: the BRIO and Baccalaureate instruments measure digital competence differently, and the comparison between them is directional, not absolute.

The fifth limitation concerns omitted variables. The regression model explained 16.2% of the variance in the score, which means that over 80% of the variation remains unexplained by the factors observable in the open data. Important determinants of digital competence, the socio-economic level of the family, access to devices and connection at home, the concrete quality of the instruction received, attitudes towards technology, are not available in the data and would very probably explain a substantial part of the residual variation. The results should therefore be read as a description of the gaps on the observable dimensions, not as a complete model of the determinants of digital competence.

6.2. Future research directions

The first direction, the most valuable, is obtaining the correspondence between the SIIIR codes of school units and counties, which would permit fine territorial analysis and multilevel modelling, separating the variation between students, between schools, and between counties. Such an analysis could directly confront the Baccalaureate data with the county benchmarks of the BRIO assessment.

The second direction is longitudinal: repeating the analysis on successive graduate cohorts, as the open data are published annually, would transform this static snapshot into a tracking of the evolution of the gaps over time and would permit evaluating the effectiveness of any interventions (Cristache, N et all, 2013). The third direction would be the disaggregation of the score across the competence domains of the DigComp framework, should the data permit it in the future, in order to identify exactly which dimensions of digital competence generate the observed gaps, information essential for the design of targeted interventions.

6.3. Conclusions

The study drew on two independent sources of real data to map the digital competence of Romanian high-school graduates. The general level proved modest, a mean score of 48.9 out of 100, with over half of candidates below the 50-point threshold, confirming, at the scale of the entire graduate cohort, the system-level diagnosis of the BRIO national assessment.

The principal analytical contribution is the ranking of the factors of inequality. The educational track, track, profile, specialisation, is the dominant factor, with differences of over 31 points between profiles. Area of residence is a secondary but consistent factor, persistent after control, with a rural–urban gap of nearly 7 points confirmed by both sources. Gender is a minor factor, with effects of differing direction in the two instruments. Digital competence integrates coherently into general school performance, with which it correlates moderately.

The conclusion for educational policy is that reducing the digital inequality of graduates requires intervention on two levels simultaneously: strengthening digital competences in the deficient tracks and profiles, which would reduce the largest gap, that between tracks; and investing in the infrastructure and human resources of rural schools, which would reduce the residual gap, that between areas. The open Baccalaureate data, published annually, offer the instrument for monitoring the effectiveness of these interventions over time, a system-level diagnostic resource that this study has sought to put to use.

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