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Digital Transformation of Education: From Infrastructure to Competences

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ABSTRACT This article proposes and empirically tests an integrated approach to monitoring university digital transformation in a single-institution setting. The approach combines the measurement of students' digital competence (Digital Competence Index, DCI) and teachers' digital pedagogical competence (Digital Competence in Education, DCEdu) with selected indicators of course process quality and digital governance practices. The study is based on two standardised online surveys administered in the LMS Moodle environment (students: n = 386; teachers: n = 89), with index normalisation to a 0–100 scale and domain decomposition. The results revealed substantial internal heterogeneity in students' digital competence and marked inter-faculty differentiation in DCI, primarily associated with the size of the lower segment of the distribution. The largest differences in DCI were associated with accessibility barriers, internet stability, and regularity of interaction with the LMS. For teachers, the aggregated DCEdu index appeared relatively insensitive to basic infrastructure conditions but showed strong variation across pedagogical governance variables, especially the formalisation of rules for students' use of generative artificial intelligence and cyber hygiene training. The study formulates a set of institutional recommendations focused on minimum course standards, authentic rubric-based assessment, formal regulations for the use of generative AI, and mandatory training in cyber hygiene and data management.

KEYWORDS digital transformation; higher education; Moodle; digital competence; DigCompEdu; learning analytics; assessment rubrics; generative artificial intelligence; academic integrity; cybersecurity.

I. INTRODUCTION

The scaling of digital technologies in higher education over the past decade has changed the "architecture" of the educational process: from the occasional use of individual tools to platform-centric models in which LMS, cloud services, digital assessment, and support for self-regulated learning function as an interconnected environment [6, 23]. At the same time, empirical conclusions regarding the effectiveness of digital learning remain inconsistent: Positive effects on success and engagement often emerge only under conditions of high-quality pedagogical design, adequate interaction, and organisational support, whereas "digitalisation as such" does not guarantee results [2, 21, 23]. This shifts the focus of research and management from the mere existence of technologies to the parameters of their pedagogical implementation.

Modern literature is increasingly focusing on the transition from the issue of "access to technology" to the issue of controllability of digital learning quality: transparent criteria, standardised indicators, and procedures for ensuring the quality of online courses [9]. In quality assurance models, the measurable characteristics of course structure, assessment, feedback, support, and service components become central, as does the operationalisation of "successful digital design" through a set of reproducible course features [9, 13]. Accordingly, sustainable learning outcomes are formed through a combination of pedagogical affordances (interactivity, active knowledge construction, learning support) with technological implementation; therefore, the key factor is the measurability of digital course parameters, not just self-assessment of satisfaction [13, 23].

Simultaneously, the concept of 'digital transformation of institutions' is developing. It interprets digitalisation as a programme of organisational change: data management, platform interoperability, human resources policy, digital culture, and decision-making mechanisms [6]. A summary of digital transformation practices in higher education institutions emphasizes the typical 'implementation gap': Universities frequently invest in infrastructure prior to establishing sustainable digital management practices, resulting in technological capabilities not being converted into educational outcomes [6]. This requires simultaneous analysis of competencies, process quality and governance rules that connect technology with results.

The critical 'key variable' of digital transformation is the digital competence of students and teachers. For teachers, digital competence is not limited to mastering tools; it includes digital pedagogical design, assessment, interaction organisation, inclusiveness, data management, and support for academic integrity, as reflected in both systematic reviews of teacher competencies and specialised frameworks for higher education [5, 20]. For students, it is becoming increasingly important to shift from declarative statements to validated measurement scales that facilitate metric monitoring, comparisons between groups, and verification of the psychometric quality of indicators [15, 21]. The conceptual basis for such metrification is provided by international frameworks for digital competences – DigComp 2.2 for citizens and DigCompEdu for educators – which enhances the comparability of indicators across the domains of 'information and data', 'interaction', 'content', "safety" and 'problem solving' [19, 22].

In the present study, DigComp 2.2 and DigCompEdu were used as conceptual frameworks for questionnaire construction and domain mapping rather than as direct scoring instruments. Student items were grouped to reflect the DigComp 2.2 dimensions of information and data literacy, communication and interaction, digital content creation, safety, and problem solving. Teacher items were structured in line with DigCompEdu-informed dimensions of digital resources, teaching design and interaction, assessment and analytics, inclusion and accessibility, and the development of students' digital competence and academic integrity. This framework-based design was intended to improve the conceptual transparency and comparability of the composite indices.

It is also important to consider empirical and institutional evidence from the Ukrainian university environment, which specifies the mechanisms for building digital competencies in an 'ecosystem' logic. Specifically, in the SMART-TNPU case study, digital transformation is described as an integrated educational and scientific ecosystem where technological infrastructure (local and cloud digital space), organizational centres and corporate standards, content solutions, and monitoring procedures are interconnected components that support the digital environment and the development of student and staff competencies [10]. Complementarily, research on the development of students' digital competence in the context of using artificial intelligence technologies records low initial awareness of AI tools among first-year students and proposes a learning trajectory with the integration of AI into professional disciplines and a special course. Importantly, the authors link the scaling of AI practices directly to the requirements of academic integrity and the formation of critical thinking, thereby placing 'AI competence' in the realm of managed educational interventions [9]. Collectively, these results reinforce the thesis that digital competencies and AI practices grow not only through individual 'mastery of tools,' but through an institutionally organised environment, standards, and monitoring, i.e., through a managed ecosystem of digital transformation [9, 10].

An important component of digital transformation is data-driven measurement – the ability of an institution to convert 'traces' of learning activities (LMS logs, course activity, assessment results, interaction indicators) into manageable decisions. Reviews of learning analytics emphasise that the effect is only possible with a comprehensive data ecosystem: agreed metrics, data quality procedures, ethical restrictions, and pedagogical intervention mechanisms [3]. Within this logic, digital assessment – in particular, automated assessment of text responses in post-school education – is seen as a component of the instrumental infrastructure for quality and scaling feedback [7]. An additional catalyst has been the emergence of generative artificial intelligence, which simultaneously expands the possibilities for personalisation and teaching support and increases the risks to academic integrity, privacy, model bias, and skill "erosion" when used unsupervised. These risks and opportunities are systematically described in conceptual works, reviews, and systematic reviews on ChatGPT/LLM in education [1, 4, 8] 12, 14, 16]. In this study, generative AI is examined not as an analytical model or predictive system, but as an institutional and pedagogical object of regulation, reflected in teachers' rules for students' use of GenAI and in students' understanding of integrity-related AI practices. In this context, cybersecurity ceases to be purely an IT task and becomes a component of educational resilience linked to institutional policies, behavioural practices and staff training. Empirical models link policies/behaviour to security performance in distance learning, and reviews summarise effective cyber training formats [17, 18].

Despite the significant amount of research, a methodological gap remains: digital transformation is mostly analysed in a fragmented manner – separately measuring (a) competencies [5, 15, [20]–[22], (b) the quality of online courses and design [9], [13], (c) analytics and data [3], (d) digital assessment practices [7], (e) policies and consequences of using generative AI [1], [4], [8], [12], [14], [16] and (f) cyber risks and cyber preparation [17] [18]. In contrast, university-level management requires an integrated measurement framework that allows for the following simultaneously: (1) assess the competence of students and teachers in comparative metrics; (2) record the process quality of course implementation in LMS; (3) assess governance components (AI usage rules, integrity, cyber hygiene, data handling); (4) perform inter-faculty benchmarking as a basis for targeted development policy.

The aim of this study is to develop and empirically test an integrated institutional approach to monitoring university digital transformation on the basis of two standardised surveys of students and teachers. The proposed design combines DCI (Digital Competence Index), DCEdu (Digital Competence in Education), domain sub-indices, and selected process/governance indicators related to LMS Moodle, generative AI usage rules, and cyber hygiene. The analytical purpose of this framework is not universal statistical generalisation, but institution-level diagnosis, inter-faculty benchmarking, and the identification of actionable directions for digital development policy.

The contribution of this study is threefold. First, it proposes a reproducible framework-based metric scheme for DCI and DCEdu with 0–100 normalisation and domain decomposition informed by international digital competence frameworks. Second, it integrates competence indicators, digital course process indicators, and governance-sensitive variables into a single analytical structure for faculty-level benchmarking. Third, it translates the empirical results into institutional recommendations concerning course standardisation, authentic assessment, formal regulation of generative AI use, and cyber hygiene training [9], [17], [18].

The remainder of the article is organised as follows. Section II presents the materials and methods. Section III reports the empirical results. Section IV discusses the findings in relation to the literature and the logic of institutional digital transformation. Section V formulates practical implications and institutional recommendations. Section VI concludes and outlines directions for further research.

II. MATERIALS AND METHODS

A. RESEARCH DESIGN AND INSTITUTIONAL CONTEXT

The study was conducted using a cross-sectional design based on two standardised online surveys at Ternopil Volodymyr Hnatiuk National Pedagogical University. The study was designed as an institutional case study intended for within-university diagnosis and benchmarking rather than for universal statistical generalisation to all higher education institutions. The institutional context is methodologically significant because digital learning is implemented systematically: courses are delivered through LMS Moodle, and assessment is carried out using the platform's tools (testing and/or submission of work with subsequent assessment). Under such conditions, the infrastructure component of digitalisation is a necessary but relatively constant condition that enables the analysis to focus on user competencies, the quality of digital course processes, and governance practices that determine the effectiveness and security of the digital educational environment.

B. DATA SOURCES, SAMPLING AND ETHICS

Only respondents who provided informed consent were included in the analysis. The student survey yielded 386 consented responses, of which 385 contained faculty identification and therefore formed the basis for faculty-stratified analysis. The teacher dataset included 89 consented responses. All 10 faculties of the university were represented in each analytical array. Data were collected anonymously without personal identifiers and analysed in aggregated form at the group and faculty levels. The study was designed to support institution-level comparison across faculties and respondent groups rather than population-level inference beyond the analysed university.

C. TOOLS AND VARIABLES

The questionnaires are structured according to the logic of 'user – process – governance/risks' in order to measure not only individual skills, but also the context of their implementation in digital learning. Questionnaire construction followed a framework-to-item logic. Student items were designed in alignment with DigComp 2.2-informed domains, whereas teacher items were constructed in line with DigCompEdu-informed domains. Thus, the questionnaires were not assembled as ad hoc lists of questions, but as framework-consistent measurement instruments intended to support domain-based aggregation and comparative interpretation.

- Profile and digital access: faculty, level/position, format of learning/teaching, main device, internet stability, accessibility needs.
- Competency scales (0–4): ordinal ratings, where 0 corresponds to the absence/instability of a skill, and 4 corresponds to autonomous and reproducible performance.
- Student block (18 points, Q10–Q27): work with information/data, communication and interaction, digital tools and content, security and privacy, problem solving and tool selection.
- Faculty block (12 points, Q37–Q48): digital resources, design and interaction, digital assessment and analytics, inclusiveness, development of students' digital skills and integrity, integrated digital maturity.
- Process and governance indicators: parameters for implementing courses in Moodle (structure, clarity of requirements, feedback, rubrics), practices for using generative AI and the existence of rules for students, cyber hygiene (training/instruction) and practices for secure data handling and access.

Moodle process assessments were recorded on five-point Likert scales, multiple-choice and frequency questions (barriers, tools, scenarios) were analysed using proportions and binary indicators by category. Generative AI was not used as an analytical model in this study, and no neural network was trained, validated, or tested. In this paper, AI is analysed as an institutional and pedagogical variable through teachers' rules for students' use of generative AI and students' understanding of integrity-related AI practices.

D. CONSTRUCTION OF COMPOSITE METRICS DCI AND DCEDU (NORMALISATION 0–100)

To ensure comparability of indicators, all indices are normalized to the range of 0–100. Equal item weighting was adopted as the most transparent and reproducible aggregation rule in the absence of external calibration weights or a latent-variable estimation design.

Digital Competence Index (DCI) for students. Let $x_{ij} \in \{0,1,2,3,4\}$denote the response of student $i$to item j, and let $m_i$denote the number of valid student competency items available for that respondent. Then

$$\bar{x}_i = \frac{1}{m_i} \sum_{j=1}^{m_i} x_{ij} , \tag{1}$$

$$DCI_i = \frac{\bar{x}_i}{4} \cdot 100. \tag{2}$$

Equivalently,

$$DCI_i = \frac{100}{4m_i} \sum_{j=1}^{m_i} x_{ij} . \tag{3}$$

The index uses equal weighting of items as the most transparent and reproducible approach in the absence of external calibration weights. This formulation normalizes the composite score to a 0–100 scale and preserves comparability across respondents with valid but partially incomplete response profiles. DCI domain sub-indices were calculated as normalized averages of the corresponding subsets of items.

- Information and data: Q10–Q13
- Communication and interaction: Q14–Q17
- Digital content and tools: Q18–Q21
- Security and privacy: Q22–Q25
- Problem solving and tool selection: Q26–Q27

Digital Competence in Education (DCEdu) for faculty. Let $y_{ij} \in \{0,1,2,3,4\}$denote the response of teacher $i$to item j, and let $k_i$denote the number of valid teacher competency items available for that respondent. Then

$$\bar{y}_i = \frac{1}{k_i}\sum_{j=1}^{k_i} y_{ij}\,, \tag{4}$$

$$DCEdu_i = \frac{\bar{y}_i}{4}\cdot 100. \tag{5}$$

Equivalently,

$$DCEdu_i = \frac{100}{4k_i}\sum_{j=1}^{k_i} y_{ij}\,. \tag{6}$$

As with DCI, the index uses equal weighting of items as the most transparent and reproducible approach in the absence of external calibration weights. This formulation normalises the composite score to a 0–100 scale and preserves comparability across respondents with valid but partially incomplete response profiles. DCEdu domain sub-indices were calculated as normalised averages of the corresponding subsets of items.

- Digital resources and copyright: Q37–Q38
- Learning design and interaction: Q39–Q40
- Digital assessment and learning analytics: Q41–Q42
- Inclusion and accessibility: Q43–Q44
- Development of students' digital skills and academic integrity: Q45–Q47
- Integrative digital pedagogical maturity: Q48

Item Q48 was retained in the overall DCEdu index as an integrative indicator of digital pedagogical maturity. If domain-level reporting is restricted to multi-item components, this item should be interpreted as part of the overall integrative profile rather than as a standalone domain with independent reliability properties.

E. DATA PROCESSING, ABSENCE AND QUALITY CONTROL

Records without informed consent were excluded. Values 0–4 were stored as numerical values but were interpreted as ordinal values in inference procedures. For multiple-choice questions, frequencies were constructed, and, where necessary, binary variables were constructed for options.

To avoid distortion of composite indices in the case of incomplete responses and simultaneously minimise the loss of observations, the minimum completeness rule was applied:

- DCI was calculated based on the presence of at least 15 out of 18 points;
- DCEdu was calculated based on the presence of at least 11 out of 12 points.

In the further analysis of relationships and inter-faculty differentiation, only observations with validly calculated indices were used.

For faculty-stratified analysis, only responses containing faculty identification were retained in the corresponding analytical subset.

F. RELIABILITY OF SCALES

Internal consistency was assessed using Cronbach's alpha. Let Kdenote the number of items in the scale, let s_j^2denote the variance of item j, and let s_T^2denote the variance of the total score. Then

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{j=1}^{K} s_j^2}{s_T^2}\right). \tag{7}$$

For the student scale (18 items), Cronbach's alpha was 0.916based on complete observations. For the teacher scale (12 items), Cronbach's alpha was 0.871. These values indicate high internal consistency and support the use of DCI and DCEdu as stable composite indices for comparative institutional analysis.

Because the present study is based on framework-informed composite indices rather than a full latent-variable structural model, Cronbach's alpha is used here as the primary reliability indicator. Additional validity diagnostics such as Composite Reliability (CR) or Average Variance Extracted (AVE) may be considered in future extensions of the design or in a dedicated psychometric appendix.

G. HETEROGENEITY METRICS AND THRESHOLDS

To describe inter-faculty differentiation, the analysis compared faculty-specific average values of the composite index and examined the spread between higher- and lower-performing faculty groups. In addition, the proportions of respondents exceeding the thresholds of 50, 75, and 90 points were calculated as operational markers of basic, advanced, and high competence suitable for institutional monitoring and benchmarking.

H. STATISTICAL ANALYSIS

Because the questionnaire responses were ordinal and the study was designed as an exploratory associational case study, non-parametric methods were used. Descriptive reporting relied on medians and interquartile ranges (Q1–Q3) as robust summaries of the central 50% of the distribution. These intervals were used for descriptive profiling only and were not interpreted as evidence of causal effects.

Inferential analysis included the Kruskal–Wallis test for multi-group comparisons, the Mann–Whitney U test for two-group comparisons, and Spearman's rank correlation for monotonic associations between composite indices and process/governance indicators. Spearman's rho was interpreted strictly as an association measure rather than as a causal coefficient. Statistical significance was evaluated at $\alpha = 0.05$. Effect sizes were reported to support substantive interpretation of statistically significant differences.

I. COMPUTING ENVIRONMENT AND REPRODUCIBILITY

Data processing, index calculation, descriptive statistics, and non-parametric tests were performed in Python using the pandas, numpy, and scipy libraries. The filtering logic, index normalisation rules, item-to-domain mapping, minimum completeness criteria, and test specifications were defined prior to final comparative analysis, which supports the reproducibility of the institutional monitoring framework.

III. RESULTS

The empirical base was formed from two standardised surveys with a prior informed-consent filter. For students, 386 questionnaires were received; 385 contained faculty identification and therefore constituted the basis for faculty-stratified analysis. Within this subset, the composite DCI index was validly calculated in 368 cases (95.6%). For teachers, 89 questionnaires were included in the analysis, and the DCEdu index was validly calculated for all respondents (100%).

Table 1. Structure of the student sample and validity of the DCI index by faculty (n = 385)

Faculty	n	Share, %	DCI valid, n	DCI validity, %	DCI invalid, n
Faculty of History	87	22.6	87	100.0	0
Faculty of Pedagogy and Psychology	66	17.1	64	97.0	2
Faculty of Arts	38	9.9	26	68.4	12
Faculty of Philology and Journalism	37	9.6	37	100.0	0
Faculty of Geography	28	7.3	26	92.9	2
Faculty of Engineering Education	27	7.0	27	100.0	0
Faculty of Physical Education	26	6.8	26	100.0	0
Faculty of Physics and Mathematics	26	6.8	25	96.2	1
Faculty of Chemistry and Biology	26	6.8	26	100.0	0
Faculty of Foreign Languages	24	6.2	24	100.0	0
Total	385	100.0	368	95.6	17

The sample structure provides sufficient analytical coverage for inter-faculty comparison, with at least 24 questionnaires in each faculty. At the same time, the completeness of the DCI block is heterogeneous. The Faculty of Arts shows lower validity (68.4%), which requires faculty-level interpretation to rely on the effective number of valid indices rather than on nominal questionnaire volumes.

To summarise the overall competence levels, descriptive statistics of the composite indices (0–100 points) are reported below. Q1 denotes the 25th percentile and Q3 the 75th percentile; the interval [Q1; Q3] represents the central 50% of the distribution.

Table 2. Descriptive statistics of composite indices and reliability of scales (0–100 points)

Index	n (valid)	Mean	SD	Median	Q1	Q3	Min	Max	Cronbach's α (n complete)
DCI (students)	368	67.78	18.51	68.06	52.78	80.56	0.00	100.00	0.916 (351)
DCEdu (teachers)	89	72.39	19.20	72.92	56.25	89.58	25.00	100.00	0.871 (87)

The distributions in Table 2 indicate substantial heterogeneity of digital competencies within the university. For students, the mean DCI (67.78) and median (68.06) are combined with a wide interquartile range [52.78; 80.56] and a noticeable lower segment (DCI < 50) amounting to 15.49%. This pattern suggests the presence of a group of students for whom autonomous performance of typical digital learning tasks remains unstable without targeted support. At the same time, 26.90% of students reach DCI ≥ 80, which indicates an internal resource for peer-supported learning and the diffusion of effective digital practices.

For teachers, the central tendency of DCEdu is higher (mean 72.39; median 72.92), while variability also remains substantial, as reflected in the interquartile range [56.25; 89.58]. The share of DCEdu < 50 equals 12.36%, which supports differentiated professional-development trajectories according to levels of digital pedagogical maturity. High values are observed in a considerable proportion of teachers (DCEdu ≥ 80: 33.71%; DCEdu ≥ 90: 23.60%), which creates a basis for mentoring, internal expertise in course quality, and the standardisation of digital assessment practices.

The internal consistency of both scales is high (DCI α = 0.916; DCEdu α = 0.871). Therefore, the composite indices are suitable for comparative institutional analysis and further structural interpretation. To identify development priorities, it is necessary not only to record overall levels but also to localise the components associated with lower quartiles and broader dispersion. The next step therefore presents the domain-level decomposition of DCI and DCEdu.

Table 3. Domain sub-indices of digital competencies (0–100 points)

Group	Domain	n	Mean	SD	Median	Q1	Q3
Students (DCI)	Information and data literacy	368	67.21	20.33	70.00	53.75	80.00
Students (DCI)	Communication and interaction	368	65.34	21.34	62.50	50.00	81.25
Students (DCI)	Digital content and tools	368	71.01	21.43	75.00	58.33	91.67
Students (DCI)	Security and privacy	368	69.12	22.04	68.75	50.00	87.50
Students (DCI)	Problem solving and tool selection	368	66.54	24.28	75.00	50.00	87.50
Teachers (DCEdu)	Digital resources and copyright	89	79.49	19.52	87.50	62.50	100.00
Teachers (DCEdu)	Learning design and interaction	89	76.12	21.95	75.00	58.33	100.00
Teachers (DCEdu)	Assessment and analytics	89	72.19	21.30	75.00	62.50	87.50
Teachers (DCEdu)	Accessibility and individualisation	89	79.92	18.33	75.00	62.50	100.00
Teachers (DCEdu)	Development of students' digital skills and academic integrity	89	59.08	34.58	66.67	33.33	100.00

The domain decomposition in Table 3 clarifies which components contribute most strongly to the overall values of the composite indices and where the main constraints are concentrated. Among students, the lowest central tendency is observed in the domain of communication and interaction (median 62.50; Q1 = 50.00), which suggests weaker skills related to collaborative work, digital interaction, and the coordination of learning-related communication. By contrast, the domain of digital content and tools shows higher values (median 75.00; Q3 = 91.67), indicating that instrumental work with digital materials is, on average, more developed than interaction-related practices. The largest dispersion is observed in problem solving and tool selection (SD = 24.28), which points to substantial heterogeneity in students' autonomy when choosing and adapting digital solutions.

For teachers, the domain profile is more contrasting. Higher values are observed in digital resources and copyright as well as accessibility and individualisation (both with Q3 = 100.00), which is consistent with established practices of preparing teaching materials and accommodating student needs. At the same time, the lowest values are observed in the domain of developing students' digital skills and academic integrity (mean 59.08; SD = 34.58; Q1 = 33.33). This pattern suggests that the integration of digital literacy, academic integrity, and responsible technology use is uneven across teachers rather than uniformly weak across the faculty as a whole.

The domain profile presented above should be complemented by a faculty-level view of DCI in order to determine whether inter-faculty differences represent a structural feature of educational environments within the university. Table 4 therefore reports faculty-specific DCI distributions in terms of central tendency, quartiles, and threshold structure.

Table 4. DCI by faculty: central tendencies and threshold structure (0–100 points)

Faculty	n (questionnaires)	n (DCI valid)	Mean	SD	Median	Q1	Q3	DCI < 50, %	DCI ≥ 80, %	DCI ≥ 90, %
Faculty of Pedagogy and Psychology	66	64	77.62	15.09	77.08	69.10	89.24	4.69	45.31	25.00
Faculty of Geography	28	26	76.02	13.57	76.43	75.00	83.09	7.69	34.62	15.38
Faculty of Philology and Journalism	37	37	74.21	19.30	76.39	58.33	90.28	8.11	43.24	27.03
Faculty of History	87	87	71.42	18.63	75.00	60.42	84.03	11.49	31.03	14.94
Faculty of Engineering Education	27	27	67.70	20.53	68.06	50.69	86.11	14.81	37.04	14.81
Faculty of Foreign Languages	24	24	61.81	19.96	68.06	48.26	75.35	29.17	16.67	4.17
Faculty of Physics and Mathematics	26	25	61.83	12.84	56.94	52.78	70.83	8.00	8.00	4.00
Faculty of Arts	38	26	58.44	11.39	55.56	52.78	63.19	23.08	3.85	0.00
Faculty of Physical Education	26	26	51.46	15.70	51.39	44.79	56.60	42.31	3.85	0.00
Faculty of Chemistry and Biology	26	26	51.01	6.78	51.39	46.18	52.78	34.62	0.00	0.00

The faculty distributions of DCI in Table 4 demonstrate not only differences in central tendency but also different profiles of internal heterogeneity. The upper cluster is formed by the Faculties of Pedagogy and Psychology, Geography, Philology and Journalism, and History, where comparatively high medians are combined with relatively elevated lower quartiles. This pattern suggests broader and more evenly distributed digital preparedness rather than the presence of only a limited high-performing subgroup. At the opposite end of the distribution are the Faculties of Physical Education and Chemistry and Biology, both with a median of 51.39. In the Faculty of Chemistry and Biology, this comparatively low level is accompanied by low variability, which points to a consistently lower centre of distribution rather than to the influence of a few isolated weak observations. A distinct profile is observed in the Faculty of Engineering Education, where the average level is combined with pronounced internal dispersion.

The threshold structure shown in Table 4 helps clarify the pattern of inter-faculty differences. These differences are associated primarily with the proportion of the lower segment (DCI < 50), which reaches 42.31% in the Faculty of Physical Education and 34.62% in the Faculty of Chemistry and Biology, compared with 4.69% in the Faculty of Pedagogy and Psychology. The upper segment (DCI ≥ 80) is most strongly represented in the Faculties of Pedagogy and Psychology and Philology and Journalism. From the perspective of institutional development policy, this suggests that some faculties primarily require strengthening of the baseline competence level for a substantial share of students, whereas others require measures aimed at reducing internal polarisation and improving the lower quartile of the distribution.

To move from the faculty-level profile to possible channels associated with competence development, it is useful to examine how DCI varies across contextual learning conditions related to accessibility, infrastructure constraints, and intensity of interaction with the LMS. The corresponding robust distributions are reported in Table 5.

Table 5. DCI by contextual learning conditions (median [Q1; Q3])

Factor	Category	n	Median [Q1; Q3]
Learning format	Full-time	250	72.22 [55.56; 83.33]
Learning format	Blended	70	56.25 [51.74; 75.00]
Learning format	Distance	47	63.89 [54.98; 84.03]
Main device	Laptop	118	75.00 [55.56; 84.80]
Main device	Combination	98	73.61 [62.68; 84.72]
Main device	Smartphone	117	63.89 [48.61; 79.17]
Main device	PC	17	52.78 [47.22; 55.56]
Main device	Tablet	15	54.41 [50.69; 58.33]
Internet stability	Stable	124	75.00 [55.56; 87.50]
Internet stability	Mostly stable	188	70.14 [56.94; 79.17]
Internet stability	Unstable	33	52.78 [50.00; 61.11]
Internet stability	Frequently absent/ restricted	22	53.47 [48.61; 58.68]
Frequency of work in Moodle	Everyday	125	73.61 [58.33; 87.50]
Frequency of work in Moodle	2–3 times a week	175	70.83 [52.78; 80.56]
Frequency of work in Moodle	Once a week	42	53.47 [48.61; 65.97]
Frequency of work in Moodle	Rarely	23	55.56 [46.53; 65.97]
Need for accessibility support	No	283	75.00 [58.33; 84.72]
Need for accessibility support	I can contact support services	42	55.56 [51.39; 64.58]
Need for accessibility support	Yes	41	52.78 [50.00; 56.94]

The distributions reported in Table 5 show that DCI varies substantially across contextual learning conditions. The largest observed differences are associated with accessibility ($H(2) = 50.06$; $p < 0.001$; $\varepsilon^2 = 0.132$). The median DCI equals 75.00 among students without adaptation needs and declines to 52.78 among those reporting such needs. The intermediate category, “I can contact support services,” does not eliminate this gap. This pattern suggests that accessibility-related constraints are institutionally relevant and are not fully offset by the mere availability of support contact points.

A second cluster of differences is associated with infrastructure and intensity of interaction with the LMS. Internet stability is linked to substantial variation in DCI ($H(3) = 29.32$; $p < 0.001$; $\varepsilon^2 = 0.073$), with a median of 75.00 for stable access and 52.78 for unstable access. Frequency of Moodle use shows a similar pattern ($H(3) = 30.28$; $p < 0.001$; $\varepsilon^2 = 0.076$): daily interaction is associated with a median of 73.61, whereas a “once a week” pattern is associated with 53.47. These results suggest that weaker infrastructure conditions and less regular engagement with the LMS are linked to lower autonomy in digital learning practices.

Material access configuration is also associated with substantial variation ($H(4) = 35.03$; $p < 0.001$; $\varepsilon^2 = 0.086$). Laptop-based access is associated with the highest median DCI, whereas smartphone, tablet, and PC categories display lower median values, although the smaller subgroup sizes call for caution in interpretation. By contrast, learning format shows a comparatively smaller association with DCI ($H(2) = 8.87$; $p = 0.012$; $\varepsilon^2 = 0.019$). Overall, Table 5 suggests that the most pronounced differences in DCI are associated less with the formal mode of learning and more with accessibility barriers, internet stability, and regularity of digital participation.

After identifying the contextual conditions associated with student DCI, the next question concerns whether a similar pattern is visible for teachers’ digital pedagogical competence. Table 6 therefore presents the distribution of DCEdu across organisational and infrastructural teaching conditions.

Table 6. DCEdu by contextual teaching conditions (median [Q1; Q3])

Factor	Category	n	Median [Q1; Q3]
Teaching format	Full-time	50	73.96 [52.08; 82.81]
Teaching format	Blended/distance	39	70.83 [63.54; 90.62]
Main device	Laptop/PC	48	73.96 [52.08; 88.02]
Main device	Combination	41	70.83 [62.50; 89.58]
Internet stability	Stable	66	75.00 [54.69; 91.15]
Internet stability	Not completely stable	23	68.75 [61.46; 83.33]
Sufficiency of IT support	Low (1–2)	8	67.71 [60.42; 75.00]
Sufficiency of IT support	Average (3)	24	66.67 [53.65; 90.10]
Sufficiency of IT support	High (4–5)	53	75.00 [62.50; 91.67]
Standardisation of course structure	Low (1–2)	22	67.71 [60.94; 91.15]
Standardisation of course structure	Average (3)	13	66.67 [56.25; 83.33]
Standardisation of course structure	High (4–5)	54	75.00 [56.77; 91.67]

The distributions reported in Table 6 suggest that teachers’ digital pedagogical competence varies less strongly across basic organisational and infrastructural conditions than student DCI does across learning conditions. Medians for full-time and blended/distance teaching formats are close, and the corresponding quartile ranges overlap substantially. This pattern suggests that teaching format itself is not a major source of differentiation in DCEdu within the analysed institutional setting.

A similar pattern is observed for the main device. Laptop/PC-based access and combined access produce comparable medians and interquartile ranges. At the level of the aggregated DCEdu index, this suggests that material access configuration is less strongly associated with the outcome than in the student sample. This is consistent with the substantive logic of DCEdu, which captures primarily pedagogical actions such as interaction design, assessment, analytics, and inclusiveness.

Internet stability is associated with a moderate shift in the median, but the quartile ranges remain overlapping. This suggests that internet-related constraints may affect continuity and convenience of teaching, yet they do not by themselves create sharply distinct competence strata within the teacher sample. From an institutional perspective, this means that infrastructure remains a necessary condition, but not a sufficient mechanism for improving digital pedagogical competence.

The most policy-relevant pair of conditions is IT support and course structure standardisation. Higher levels of both are associated with somewhat higher medians, although the broad interquartile ranges indicate that these variables should be interpreted as enabling conditions rather than direct determinants of competence. The presence of teachers with high DCEdu values even under lower support or standardisation conditions suggests an important role for individual pedagogical capacity, whereas the rise in medians under higher-support and higher-standardisation conditions points to an institutional facilitation effect.

The summary of Table 6 suggests that aggregated DCEdu is less differentiated by infrastructure and organisation than by pedagogically meaningful governance-related variables. The next block of results therefore turns to those governance-sensitive indicators.

Regulatory practices in digital teaching appear to be among the strongest factors associated with variation in the Digital Competence in Education Index (DCEdu). To examine this pattern, DCEdu was compared with two pedagogical-governance indicators: the presence of rules for students’ use of generative AI within the discipline and participation in cyber hygiene training during the previous year. Robust distributions are reported through medians and quartiles (Q1, Q3).

Table 7. DCEdu by rules for students’ use of generative AI and cyber hygiene (0–100 points, median [Q1; Q3])

Factor	Category	n	DCEdu, median [Q1; Q3]
Rules for students’ use of generative AI	Yes, clearly defined	29	95.83 [81.25; 100.00]
	Partially/orally	28	71.88 [64.06; 77.08]
	No, not defined	29	54.17 [47.73; 65.91]
Cyber hygiene training over the past year	Yes	33	91.67 [81.25; 100.00]
	No	56	63.54 [51.56; 71.35]

The pattern associated with rules for students’ use of generative AI is monotonic and represents the largest observed gap in the teacher data. The transition from undefined rules to partial formalisation and then to clearly defined rules is associated with an increase in the DCEdu median from 54.17

to 71.88 and 95.83 points. The Kruskal–Wallis test confirms that these differences are statistically significant and substantively large ($H(2) = 48.36$; $p < 0.001$; $\varepsilon^2 = 0.559$).

Cyber hygiene training shows a similarly pronounced gradient. Among teachers who reported such training, the median DCEdu equals 91.67, compared with 63.54 among those who did not. The lower quartile is also higher in the trained group, indicating that the difference is not limited to the upper end of the distribution. The Mann–Whitney U test confirms a statistically significant and substantively large difference ($U = 1709$; $p < 0.001$; $r = 0.706$).

The two governance practices are also structurally related. All teachers who reported the absence of clearly defined AI-use rules belonged to the group without cyber hygiene training. At the same time, the AI-rule gradient remains visible within subgroups. Among those who received training, DCEdu is higher for teachers with clearly defined rules than for those with partial or oral rules (medians 97.92 vs. 77.08; $p = 0.00268$). Among those without training, the three rule categories also differ significantly ($H(2) = 12.25$; $p = 0.00219$; $\varepsilon^2 = 0.201$). Therefore, formalised AI-use rules and cyber hygiene training are best interpreted as complementary elements of pedagogical governance associated with higher digital pedagogical maturity.

The robustness of this interpretation was examined using an alternative DCEdu index calculated without the two items directly related to digital security and academic integrity (Q46, Q47). The effects remain statistically significant and substantively large: for AI rules, $H(2) = 43.58$; $p < 0.001$; $\varepsilon^2 = 0.501$; for cyber hygiene, $U = 1657$; $p < 0.001$; $r = 0.660$. This suggests that the observed associations are not reducible to a mechanical overlap between the content of the index and the governance variables, but rather reflect a broader profile of organisational and methodological maturity in digital teaching.

After establishing inter-faculty heterogeneity in DCI, the next question concerns which properties of the digital learning process are most strongly associated with students' competence profiles. The data suggest that the strongest observed associations are linked not to formal access parameters as such, but to course-manageability indicators that shape the clarity of the learning contract within the LMS.

Table 8. DCI associations with process and regulatory indicators of the digital course (students)

Indicator	Scale	n	Correlation with DCI (Spearman's ρ)	p
Structure of Moodle course	1–5	357	0.410	<0.001
Clarity of requirements for tasks and tests	1–5	357	0.454	<0.001
Understanding of integrity rules when using AI	0–4	341	0.499	<0.001

Substantively, the associations reported in Table 8 suggest that higher levels of course manageability are linked to more favourable DCI distributions. Student groups reporting clearer course structure and clearer task requirements are more frequently located in the upper part of the DCI distribution, whereas lower ratings of course organisation are associated with a higher proportion of lower-index observations. The strongest observed association is between DCI and understanding integrity rules in the context of AI use, which suggests that digital competence in this setting combines instrumental skills with normative literacy.

The indicator of feedback speed is also associated with DCI, although with a smaller effect size ($H(3) = 12.74$; $p = 0.0052$; $\varepsilon^2 = 0.024$). Taken together, these results suggest that the structural and instructional organisation of the digital course is more strongly associated with student competence profiles than the pace of communication alone.

Taken together, the results reported above form a coherent empirical picture of university digital transformation as the interaction of three levels: user competencies, process quality of the digital course, and regulatory governance. On the student side, DCI is characterised by marked inter-faculty differentiation and sensitivity to conditions associated with the completeness of digital participation, especially accessibility, internet stability, and regularity of LMS use. On the teacher side, the aggregated DCEdu index appears less differentiated by basic infrastructure conditions and more strongly associated with pedagogical governance variables, particularly formalised rules for students' use of generative AI and cyber hygiene training. Overall, these findings suggest that digital transformation in the analysed institutional setting is linked less to the mere availability of platforms and more to the manageability of the digital learning environment, the clarity of rules, and the presence of institutional risk-control practices.

IV. DISCUSSION

A. INTERPRETATION OF FINDINGS: FROM ACCESS THRESHOLDS TO GOVERNED DIGITAL LEARNING

The findings support a layered interpretation of university digital transformation. Infrastructure sets the threshold conditions for participation in the digital environment, yet the observed differences in competence profiles are associated more strongly with the manageability of the learning process than with the mere availability of technological resources. On the student side, the most pronounced variation in DCI is linked to accessibility conditions, internet stability, and regularity of interaction with LMS Moodle. This suggests that digital competence develops not only through exposure to digital tools, but through repeated and sufficiently stable participation in digitally organised learning.

On the teacher side, the aggregated DCEdu index appears less differentiated by baseline infrastructural conditions and more strongly associated with pedagogical governance variables. In particular, formal rules for students' use of generative AI and participation in cyber hygiene training are associated with substantially higher DCEdu values. This pattern suggests that digital pedagogical maturity is linked not only to technical readiness, but also to the institutional formalisation of responsible digital teaching practices. In that sense, digital transformation in the analysed setting is better understood as a governed organisational process than as a simple expansion of technical provision.

B. COMPARISON WITH THE LITERATURE AND CLARIFICATION OF THEORETICAL MEANING

The findings are consistent with studies showing that the educational effects of digitalisation depend on course design quality, interaction, and institutional support rather than on technology availability alone [2], [9], [13], [23]. The observed centrality of course structure, clarity of requirements, and procedural transparency supports approaches to online learning quality assurance in which measurable elements of design and assessment are treated as core components of course effectiveness [9], [13].

The results also align with the broader literature on institutional digital transformation in higher education, especially with the idea of an "implementation gap," whereby universities often deploy platforms faster than they establish stable governance routines, quality standards, and monitoring procedures [6]. In this respect, the proposed analytical design contributes by linking three levels that are often studied separately: user competencies, process quality of digital courses, and governance-sensitive institutional practices.

Compared with studies focused exclusively on students' self-reported competence or teachers' digital skills, the present approach combines competence measurement with process and governance indicators. Compared with course-quality models, it retains a user-competence dimension. Compared with learning-analytics-only approaches, it captures institutional rules and pedagogical regulation that are not directly observable in LMS trace data. The distinctive value of the present design therefore lies in integrating user, process, and governance levels within a single institutional monitoring framework.

The findings related to generative AI and cyber hygiene are also consistent with the contemporary literature describing the dual nature of generative models in education: on the one hand, they offer pedagogical support and personalisation opportunities; on the other hand, they generate challenges related to academic integrity, privacy, bias, and responsible use [1], [8], [12], [14], [16]. Similarly, cybersecurity in educational settings is increasingly interpreted not as a purely technical issue, but as a matter of institutional risk management and behavioural discipline [17], [18].

C. CONTRIBUTION AND LIMITATIONS OF THE STUDY

The contribution of the study lies in moving from fragmented measurements toward an integrated management-oriented framework. The proposed design combines DCI, DCEdu, domain decomposition, and governance-sensitive indicators in a single analytical structure suitable for institution-level diagnosis and benchmarking. In contrast to approaches that measure competencies, course quality, or governance separately, the present model connects these dimensions within one monitoring architecture.

The study also makes a practical methodological contribution by showing that a university can construct a reproducible monitoring scheme using standardised surveys, transparent index normalisation, and non-parametric association analysis without relying on opaque predictive modelling. In this sense, the value of the proposed framework lies not only in its empirical findings, but also in its replicable institutional logic.

At the same time, the study has several limitations. First, the cross-sectional design supports group comparison and association analysis, but it does not identify causal effects. Therefore, the reported relationships should be interpreted as institutionally meaningful associations rather than as verified causal pathways. Second, the study is based on self-reported data, which may be affected by perception bias and differences in self-assessment styles. Third, the research design is limited to a single university, which restricts direct external generalisation. Fourth, some faculty-specific subgroups are smaller than others, which calls for caution when interpreting more detailed internal differences.

Further research should therefore proceed in at least three directions. The first is longitudinal monitoring of DCI and DCEdu in order to trace changes over time. The second is integration of survey data with LMS-based learning analytics to validate self-reported patterns against digital trace data. The third is inter-institutional comparison using a common DigComp-/DigCompEdu-informed logic in order to test the stability of the observed associations across different organisational and cultural settings.

V. PRACTICAL IMPLICATIONS AND RECOMMENDATIONS

The empirical results suggest that the effectiveness of digital transformation in higher education depends less on infrastructure alone than on the institutional ability of the university to formalise and reproducibly maintain the key parameters of the digital learning cycle. These parameters include course manageability, transparency and validity of assessment, regulatory certainty regarding the use of digital tools, and control of academic, privacy, cybersecurity, and data-related risks. In this perspective, practical implications can be organised around four complementary institutional levers.

A. MINIMUM STANDARD FOR DIGITAL COURSES AS A GOVERNANCE FRAMEWORK

A university-wide minimum standard for digital courses should be introduced across all disciplines in the learning management system. Its function is to ensure reproducibility of process quality regardless of faculty or teacher. At a minimum, such a standard should include a unified modular or weekly structure, clear navigation, a visible schedule of deadlines, explicit requirements for assignments and tests, fixed feedback procedures, published assessment rubrics, formal academic-integrity rules, including provisions related to generative AI, and baseline accessibility requirements.

From an institutional perspective, such a standard functions not merely as a technical template, but as a governance instrument. It reduces uncertainty in the learning contract, facilitates comparability across courses, and creates a more stable basis for monitoring and quality assurance.

B. AUTHENTIC ASSESSMENT AND RUBRIC-BASED EVALUATION

The results suggest that digital transformation should not be reduced to digitised submission or automated testing alone. Assessment should be redirected toward authentic formats that record not only the final product, but also argument quality, work with sources and data, decision logic, and the reproducibility of performance in a digital environment.

At the institutional level, this means establishing a minimum repertoire of authentic formats across disciplines, including analytical written assignments, project-based digital artefacts, oral verification elements, and group work with documented contribution procedures. Rubrics should be standardised at least at the level of core criteria such as argumentation, use of evidence, data accuracy, logical structure, reproducibility, and integrity. When published in advance, these rubrics simultaneously improve transparency, feedback quality, and the defensibility of assessment under conditions of widespread AI use.

C. FORMAL RULES FOR STUDENTS' USE OF GENERATIVE AI

One of the clearest findings of the study is that teachers' digital pedagogical maturity is strongly associated with the presence of formalised AI-use rules. This makes the regulation of generative AI a practical governance priority rather than an optional pedagogical addition.

A university-level regulatory framework should define at least four elements: permitted scenarios of use, prohibited scenarios, requirements for disclosure, and standards of factual and source verification. Permitted uses may include structuring material, linguistic or stylistic editing of one's own text, concept clarification, self-testing support, or auxiliary analysis of a provided dataset, provided the output remains reproducible and academically accountable. Prohibited uses should include hidden task completion, substitution of authorship, fabricated references, and circumvention of assessment procedures. Students should be required to declare where and for what purpose generative AI was used, and assessment criteria should explicitly include factual and source validation.

Such regulation transfers generative tools from an informal grey zone into a transparent pedagogical regime. This does not eliminate risk, but it reduces normative uncertainty and improves the quality and legitimacy of digital assessment.

D. CYBER HYGIENE AND EDUCATIONAL DATA MANAGEMENT

The results also indicate that cyber hygiene is not peripheral to digital teaching quality. It is associated with higher DCEdu values and therefore should be institutionalised as a minimum condition of professional readiness for digital education.

Annual cyber hygiene training should be mandatory for teachers and other relevant staff. It should cover authentication and access management, account protection, secure handling of educational data, privacy and data minimisation, use of external digital services, incident-response protocols, and allocation of responsibilities. In parallel, the university should adopt a formal educational data management policy defining which data are collected, for what purposes, under what access conditions, and with what ethical limitations.

Together, these steps create a legitimate basis for learning analytics, reduce the risk of uncontrolled data use, and strengthen the resilience of the digital educational environment.

VI. CONCLUSIONS

This study developed and empirically tested an integrated institutional approach to monitoring university digital transformation on the basis of two standardised surveys of students and teachers. The proposed framework combines the Digital Competence Index (DCI), the Digital Competence in Education index (DCEdu), domain-level decomposition, and selected process and governance indicators related to LMS Moodle, generative AI use, and cyber hygiene. Within the analysed university setting, the results show substantial internal heterogeneity in student digital competence and marked inter-faculty differentiation in DCI, especially in relation to accessibility, internet stability, and regularity of interaction with the LMS.

For teachers, the aggregated DCEdu index appears less differentiated by baseline infrastructural conditions and more strongly associated with pedagogical governance variables, especially formal rules for students' use of generative AI and cyber hygiene training. For students, higher DCI values are most clearly associated with indicators of course manageability, such as course structure, clarity of requirements, and normative literacy regarding integrity in AI-assisted learning. Taken together, these findings suggest that digital transformation in higher education is linked less to the mere presence of platforms and more to the manageability of the learning environment, the clarity of institutional rules, and the systematic governance of digital risks.

The scientific contribution of the study lies in proposing a reproducible framework-based metric scheme that integrates competence indices, domain decomposition, and governance-sensitive institutional diagnostics within a single analytical design. Unlike fragmented approaches that examine competencies, course quality, or governance separately, the present model connects these three dimensions in one monitoring architecture. Its practical contribution lies in showing that universities can strengthen digital competence not only by expanding the set of technologies, but by standardising digital-course quality, formalising the pedagogical use of generative AI, and institutionalising cyber hygiene and educational data governance.

At the same time, the results should be interpreted as institution-specific and associational rather than universally generalisable or causal. The cross-sectional design, self-reported data, and single-institution setting impose clear limits on inference. Further research should therefore focus on longitudinal analysis of changes in DCI and DCEdu, integration of questionnaire data with learning-analytics evidence, and inter-institutional comparisons aimed at testing the stability of the observed patterns across different organisational and cultural contexts.

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