Preparing higher education for artificial intelligence development in the evolving landscape of Industry 5.0: A study of Polish universities

Anna Sączewska-Piotrowska
University of Economics in Katowice
Katowice, Poland *anna.saczewska-piotrowska@ue.katowice.pl*

Kamila Bartuś
University of Economics in Katowice
Katowice, Poland *kamila.bartus@ue.katowice.pl*

Bartłomiej Hadasik
University of Economics in Katowice
Katowice, Poland *bartlomiej.hadasik@ue.katowice.pl*

Abstract

This study investigates the extent to which Industry 5.0-related content, technologies, and practical components are integrated into higher education institutions in Poland. The findings reveal significant disparities based on institutional type and academic profile. Technical and public universities show the highest levels of readiness for digital transformation, while pedagogical, vocational, and artistic institutions (particularly private ones) demonstrate lower integration and limited access to relevant specializations. Using multiple correspondence analysis (MCA) and hierarchical clustering (HCPC), the research identifies latent structures and clusters of institutions with distinct digital adaptation profiles. Chi-square and Cramér's V tests further confirm significant associations between institutional characteristics and Industry 5.0 readiness. The results highlight systemic inequalities and emphasize the need for differentiated policy interventions to support less advanced institutions in bridging the digital transformation gap.

Keywords: Industry 5.0, higher education, university, artificial intelligence

1. Introduction

The rapid development of artificial intelligence (AI) is evident across nearly all areas of personal and professional life, increasingly influencing how individuals learn, work, and interact. In response, the higher education sector must adapt to the evolving learning environment shaped by these advancements, including the widespread use of generative AI, to address the challenges posed by the transition to Industry 5.0 [16]. While it is evident that higher education must adapt to AI, the pressing question is whether institutions are truly doing so in practice.

The integration of AI technologies is central to Industry 5.0, as AI enables autonomous, data-driven decision-making that improves organizational efficiency and coherence [31]. In response to Industry 4.0's shortcomings, Industry 5.0 has been proposed to align technological progress with human well-being, requiring a clear understanding of current human-technology dynamics. Further research on human–AI interaction is vital for sustainable development, as Industry 5.0 both influences and is shaped by academic research and innovation [22].

To effectively operationalize the principles of Industry 5.0, it is essential that higher education institutions are adequately prepared to integrate AI and derivative technologies into their core activities [29]. In view of the inseparability of the AI concept from the development of Industry 5.0, as well as its influence on academia, this relationship warrants more thorough exploration. Moreover, as there is a scarcity of research on the preparedness of higher education institutions for

AI in this context,[1] the lack of evidence further underscores the importance of addressing this issue. As noted in [4], understanding the interplay between economy, humans, technology, and education in Industry 5.0 needs rigorous research, as stakeholder strategies are still underdeveloped.

Emerging from the considerations outlined above is a central research question that guides this study: *How are higher education institutions in Poland prepared for the advancement of AI in the context of the evolving challenges of Economy 5.0?* The regional context is particularly relevant here, as Poland offers a valuable lens through which to examine broader trends not only within the very country, but also the entire Central and Eastern European region. This study is aimed to explore the awareness and readiness of Polish universities to embrace the principles of Industry 5.0 concerning the AI-driven solutions' integration into their curricula and broad usage in scientific and didactic processes, while offering fresh insights into their transformation toward human-centric and sustainable development.

This paper is structured as follows: Section 2 reviews related literature and the theoretical foundations of AI in higher education, particularly in the context of Industry 5.0. Section 3 outlines the research methodology. Section 4 presents the study's findings, while Section 5 offers discussion, conclusions, and directions for future research.

2. Related works

Universities are increasingly redefining their role from mere knowledge producers to active societal enablers, addressing pressing social challenges through research and innovation [13]. This shift calls for a holistic educational approach, emphasizing experiential learning and interdisciplinary programs that foster critical thinking and problem-solving skills essential for the Industry 5.0 era [19]. Since AI is considered to be one of the key drivers of Industry 5.0 development [11], it is imperative that its operation is now considered at various levels. Industry 5.0 signals a shift toward integrating advanced technologies like AI while enhancing human agency and innovation [8], prompting universities to sustainably adapt their educational and operational strategies accordingly. Thus, to meet the challenges of Industry 5.0, higher education must develop effective and ethical mechanisms for the sustainable implementation of AI [27].

The fast progress of AI is creating new challenges for higher education, as it transforms long-established ways of teaching, learning, and scholarly research [21]. AI also offers new opportunities to enhance learning and skill acquisition [9], aligning with the concept of Artificial Intelligence in Education (AIEd) [23]. AIEd enables personalized learning through intelligent tutoring systems that enhance student performance [23, 35]. Baker and Smith [3] see AIEd instruments from a more broad perspective: they classify these tools into three categories: learner-facing (supporting student learning), teacher-facing (assisting with tasks like assessment and feedback), and system-facing (providing institutional-level insights).

With Industry 5.0's focus on human-AI collaboration, aligning student learning with evolving industry needs is increasingly important [10]. AI-driven skill development leverages technologies such as machine learning, natural language processing, and data analytics to create personalized, flexible learning experiences [9, 30]. These tools enable students self-paced learning, adaptive assessment, and real-time feedback, fostering competencies relevant to Industry 5.0 [35]. Recent research highlights both the benefits and challenges of using generative AI in education, noting its value for personalized learning, language development, text correction, and time management [17]. It offers instant access to explanations while promoting critical thinking and improving students' source evaluation and question formulation skills [33]. However, there are concerns about the stress and anxiety students may experience in meeting academic expectations, even as the technology offers significant potential for educational innovation [7].

[1] While some studies exist (e.g., [30, 34]), their primary focus has not been on AI within the context of Industry 5.0 in universities.

AI technologies are significantly influencing teaching methods and the operation of educational institutions. Main concerns in higher education relate to AI's use in creating academic work, including dissertations, articles, and essays [2]. Such AI-driven systems have evolved from their predecessors, and effects on administrative efficiency and cost-reduction make necessary a governing framework that directs the systems' effectiveness, ethical usage, etc. [27]. These frameworks perform a risk assessment that ensures compliance with educational values and guard against misuse by identifying potential risks [5].

Although AI can improve learning outcomes and institutional productivity, it often requires substantial financial investment, with returns that may only become evident over an extended period [1, 28]. Most importantly, adopting AI entails significant upfront costs and staff upskilling, which requires careful strategic planning. Universities should also assess their readiness for effective and sustainable implementation [1]. Effective AI integration relies on institutions mobilizing human potential, especially faculty adapting and developing AI-related skills [28].

As seen, universities' readiness to adopt AI is gaining importance, also in the context of Industry 5.0, which highlights human-centric automation and innovation. Although interest in AI integration is growing, challenges persist in areas such as institutional preparedness, governance, and ethical usage [25, 27]. Universities are developing policies to guide ethical AI use, such as ChatGPT, while balancing its benefits with the need to uphold academic integrity [24]. This is because the successful integration of AI in higher education is seen to depend on the collaboration among educators, policymakers, and technology developers to ensure alignment with ethical standards and societal values [18]. A key challenge to institutional AI readiness is faculty and staff resistance, often driven by fears of job displacement and the perceived complexity of integration [25]. Addressing this requires targeted training to build technological literacy and pedagogical confidence, enabling educators to embed AI meaningfully into curricula [14].

This study is based on the assumption that the integration of Industry 5.0 principles into higher education is not uniformly distributed across institutions. Thus, it is hypothesized that structural and organizational features, such as institutional type (public vs. private) and academic profile (e.g., technical, pedagogical), significantly influence the degree of engagement in this transformation. Based on a preliminary review of the relevant literature, the following main research hypothesis (**H1**) was formulated: *The level of engagement in the implementation of Industry 5.0-related content, digital technologies, and practical training varies significantly depending on the institutional profile and type of higher education institution*. This assumption formed the basis for the empirical analysis presented in the subsequent Section 3.

3. Methods

The analysis was based on multivariate exploratory techniques, primarily multiple correspondence analysis (MCA) and hierarchical clustering on principal components (HCPC), which allowed for the reduction of dimensionality and identification of latent structures in the data [12]. MCA was used to analyze associations between institutional characteristics, digital integration, and needs. Hierarchical clustering then grouped institutions into homogeneous classes. The v-test statistic was used to identify variables significantly overrepresented in each class and aid interpretation.

To examine the relationships between the type and profile of higher education institutions and their incorporation of Industry 5.0-related content and specializations, contingency table analysis and chi-square tests of independence were applied. Given the nominal nature of the variables, these tests were appropriate for assessing whether the observed differences in response distributions were statistically significant. In addition, Cramér's V coefficient was calculated to determine the strength of association between variables. Interpretation of the effect size followed conventional thresholds ($V \geq 0.1$ = weak; $V \geq 0.3$ = moderate; $V \geq 0.5$ = strong) [6]. All analyses and visualizations were conducted in R package using the packages *FactoMineR* [20], *factoextra* [15], *ggstatsplot* [26], and *ggplot2* [36].

The data was collected via an online questionnaire (CAWI) designed by the research team based on existing literature and expert consultations. The instrument underwent a pilot test with 10 respondents to ensure clarity and consistency. Academic staff and administrators completed the final, voluntary, and anonymized survey after email invitation.

4. Results

4.1. Sample characteristics

Table 1 presents the characteristics of the sample (N = 187). The largest group of institutions represents technical universities (33.2%), followed by universities (19.8%) and pedagogical universities (12.3%). Public institutions constitute a slight majority of the sample (52.4%), while private institutions account for 47.6%. The distribution reflects a diverse representation of higher education institutions across different academic profiles. According to data from Statistics Poland for the academic year 2023/2024 [32], there were 354 higher education institutions operating in the country. The sample covers approximately 52.8% of Polish higher education institutions, representing a substantial and representative portion of the national academic landscape.

Table 1. Sample characteristics (N=187)

Variable	Category	%
Institution	University	19.8
	Technical university	33.2
	Economic university	9.1
	Pedagogical university	12.3
	Medical university	10.7
	Art university	5.9
	Vocational university	9.1
Type	Public	52.4
	Private	47.6

4.2. Institutional advancement level

The first stage of the analysis focused on the strategic approach of higher education institutions to emerging technologies, referred to as the level of institutional advancement. As a result of the classification of higher education institutions – based on variables such as academic profile ($institution$), type of institution ($type$), the presence of a specialized digital technology unit ($unit$), and the use of artificial intelligence (AI) in administrative and scientific data analysis (adm_sci) – four clearly differentiated classes were identified. Table 2 presents the characteristics of these classes based on significantly overrepresented features (v-test > 0).

The first cluster consists almost exclusively of technical universities (v-test = 15.04), with a dominant share of public institutions (v-test = 5.19) and a strong presence of specialized organizational units dedicated to digital technologies (v-test = 7.36). This group represents technologically advanced institutions with a high level of organizational maturity in the area of digitalization. It suggests a high potential for implementing AI-based solutions.

The second cluster includes primarily general universities (v-test = 10.61) and economic universities (v-test = 6.49). The co-occurrence of these two types of institutions within the same cluster points to a shared academic profile and a similar operational model. Although there are no significant indicators of digital advancement in this group, their affiliation with this cluster may suggest a more traditional institutional character, with relatively limited involvement in technological transformation, especially in terms of AI adoption.

The third cluster is significantly overrepresented by vocational (v-test = 8.42) and art universities (v-test = 6.44). These institutions are characterized by a very low level of digital infrastructure

Table 2. Institution advancement level: Descriptions of the clusters by categories

Cluster	Cla/Mod	Mod/Cla	p-value	v-test
Cluster 1				
institution = technical	100.000	100.000	<0.001	15.038
unit = unit_yes	56.701	88.800	<0.001	7.357
type = public	50.000	79.032	<0.001	5.195
Cluster 2				
institution = university	100.000	68.519	<0.001	10.613
institution = economic	100.000	31.481	<0.001	6.492
Cluster 3				
institution = vocational	100.000	60.714	<0.001	8.417
institution = art	100.000	39.286	<0.001	6.441
unit = unit_no	28.889	92.857	<0.001	5.339
adm_sci = adm_sci_no	26.923	50.000	0.007	2.677
type = public	20.408	71.429	0.030	2.166
Cluster 4				
institution = pedagogical	100.000	53.488	<0.001	8.639
institution = medical	100.000	46.512	<0.001	7.916
type = private	42.697	88.372	<0.001	6.266
unit = unit_no	35.556	74.419	<0.001	3.926

Note: Cla/Mod = distribution of significant categories across clusters; Mod/Cla = within-cluster distribution

development – most do not have specialized units focused on digital technologies ($unit$ = no, v-test = 5.34). Additionally, this cluster includes a higher proportion of institutions that do not use AI in data analysis (v-test = 2.68), along with a predominance of public institutions (v-test = 2.17). This group includes educational institutions with a narrow teaching profile and limited resources, which may contribute to their low level of digitalization and innovation.

The fourth cluster consists mainly of pedagogical (v-test = 8.64) and medical universities (v-test = 7.92). Private institutions are significantly overrepresented in this group (v-test = 6.27), and the absence of specialized digital technology units is a defining feature ($unit$ = no, v-test = 3.93). The profile of this cluster suggests institutions with a high degree of thematic specialization but limited organizational capacity for digital development.

4.3. Modern technologies in teaching at Polish universities

The next part of the analysis examined the implementation of modern technologies in teaching, based on a multiple-choice question. The results of the clustering of higher education institutions into three classes are presented in Table 3. The analysis included variables related to the academic profile ($institution$) and the type of institution ($type$).

The first cluster includes institutions with a low level of implementation of modern digital technologies in the teaching process. Among the institutions classified in this group, private universities were significantly overrepresented (v-test = 6.85), as well as those with pedagogical (v-test = 5.94) and medical profiles (v-test = 4.81). Other profiles – artistic (v-test = 3.82), vocational (v-test = 3.68), and economic (v-test = 3.12) – also appeared in this cluster with higher-than-average frequency. A defining feature of this group is the lack of advanced technologies, such as Big Data and data analysis (BD_no, v-test = 5.35), Internet of Things (IoT_no, v-test = 4.99), artificial intelligence (AI_no, v-test = 4.18), robotics ($Robotics\_no$, v-test = 4.29), and blockchain ($Blockchain\_no$, v-test = 3.14). Despite this overall technological distance, e-learning platforms were widely used, as confirmed by the positive v-test value for this technology ($E\_learning\_yes$, v-test = 2.02). The profile of this cluster can thus be described as traditional, mainly using basic remote teaching tools and only limited advanced digital components.

Table 3. Implementation of modern technologies in teaching: Cluster characteristics

Cluster	Cla/Mod	Mod/Cla	p-value	v-test
Cluster 1				
type = private	71.9	74.4	<0.001	6.9
institution = pedagogical	100.0	26.7	<0.001	5.9
BD = BD_no	59.7	86.0	<0.001	5.4
IoT = IoT_no	53.5	97.7	<0.001	5.0
institution = medical	95.0	22.1	<0.001	4.8
Robotics = Robotics_no	53.3	94.2	<0.001	4.3
AI = AI_no	59.6	72.1	<0.001	4.2
institution = art	100.0	12.8	<0.001	3.8
institution = vocational	88.2	17.4	<0.001	3.7
Blockchain = Blockchain_no	48.6	100.0	0.002	3.1
institution = economic	82.4	16.3	0.002	3.1
E_learning = E_learning_yes	47.3	100.0	0.044	2.0
Cluster 2				
institution = technical	83.9	58.4	<0.001	7.1
type = public	69.4	76.4	<0.001	6.3
institution = university	91.9	38.2	<0.001	6.3
BD = BD_yes	65.1	46.1	<0.001	3.4
Blockchain = Blockchain_no	50.3	100.0	0.001	3.2
AI = AI_yes	57.8	53.9	0.013	2.5
Cluster 3				
Blockchain = Blockchain_yes	100.0	83.3	<0.001	7.8
IoT = IoT_yes	36.7	91.7	<0.001	5.9
Robotics = Robotics_yes	25.7	75.0	<0.001	4.3
BD = BD_yes	15.9	83.3	<0.001	3.5
AI = AI_yes	13.3	91.7	<0.001	3.4
E_learning = E_learning_no	60.0	25.0	0.002	3.1
institution = technical	12.9	66.7	0.018	2.4

Note: Cla/Mod = distribution of significant categories across clusters; Mod/Cla = within-cluster distribution

The second cluster includes more technologically advanced institutions, mainly public universities (v-test = 6.32), with a technical profile (v-test = 7.13), and general universities (v-test = 6.25). In this group, there was a notable overrepresentation of institutions using Big Data and data analysis technologies (BD_yes, v-test = 3.39) and artificial intelligence (AI_yes, v-test = 2.48). Interestingly, this cluster also includes institutions that do not use blockchain technology ($Blockchain\_no$, v-test = 3.23), which may suggest a selective approach to technology adoption, favoring well-established tools over niche or complex solutions less suited to teaching.

The third cluster represents the most digitally advanced institutions, which actively utilize modern technologies in their teaching practices. Institutions classified in this group were significantly overrepresented in the use of blockchain ($Blockchain\_yes$, v-test = 7.81), Internet of Things (IoT_yes, v-test = 5.92), robotics ($Robotics\_yes$, v-test = 4.30), Big Data and data analysis (BD_yes, v-test = 3.52), and artificial intelligence (AI_yes, v-test = 3.39). Additionally, this cluster also includes technical universities (v-test = 2.37), which confirms the dominance of institutions with a strong technological profile. A notable feature of this group is the frequent declaration of not using e-learning platforms ($E\_learning\_no$, v-test = 3.10), which may indicate a shift toward more advanced digital teaching models or the integration of technologies that go beyond traditional e-learning platforms. AI is used in technical universities, for example, through adaptive learning platforms and plagiarism detection tools. It also helps some institutions optimize course schedules and manage resources.

The next question, aimed at deepening the understanding of how modern technologies are used in the teaching process, concerned the inclusion of Industry 5.0-related content in educational programs. The results, broken down by institutional profile and type, are presented in Figure 1.

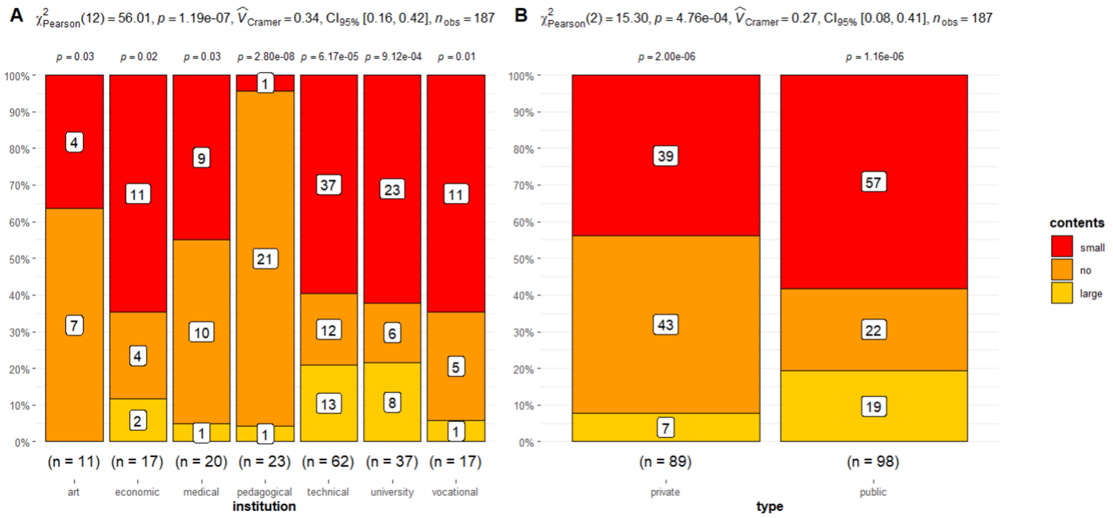

Fig. 1. Inclusion of Industry 5.0-related content in educational programs.

The relationship between the academic profile of institutions and the extent to which they incorporate Industry 5.0-related content is statistically significant ($\chi^2(12) = 56.01$, $p < 0.001$, Cramér's $V = 0.34$), indicating a moderate strength of association. The highest share of institutions not incorporating such content at all is observed among pedagogical (21 out of 23 cases) and artistic universities (7 out of 11 cases). In contrast, technical universities are more likely to report partial or extensive integration of Industry 5.0 content (50 out of 62 cases).

Additionally, institutions were asked whether their educational programs include specializations related to Industry 5.0. Figure 2 presents the distribution of responses to this question according to the institutional profile and type.

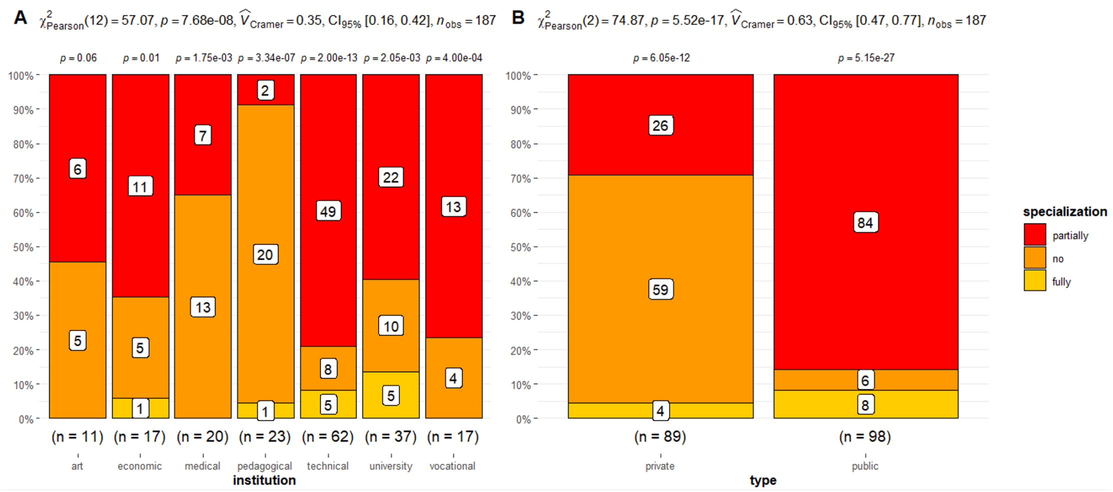

Fig. 2. Inclusion of Industry 5.0-related specializations in educational programs.

The relationship between institutional profile and the level of Industry 5.0 specialization availability is statistically significant ($\chi^2(12) = 57.07$, $p < 0.001$, Cramér's $V = 0.35$), indicating a moderate association. Technical universities are clearly leading in this regard, with 49 institutions offering partial inclusion of Industry 5.0-related specializations, and 5 offering them fully. In contrast, only isolated cases of specialization are found in pedagogical universities. Artistic, medical, and vocational institutions offer no full Industry 5.0-related specializations.

A very strong and statistically significant relationship was also found between the type of institution and specialization availability ($\chi^2(2) = 74.87$, $p < 0.001$, Cramér's $V = 0.63$), indicating a strong association. Private institutions overwhelmingly do not offer specializations related to Industry 5.0, with 59 such cases compared to 26 reporting partial and only 4 full availability. In contrast, public institutions show a more favorable picture: 84 offer partial and 8 full Industry 5.0-related specializations, though 6 still offer none. This suggests they may be more agile and responsive to digital and societal transformation.

Another aspect analyzed within this Section 4.3 was the identification of digital competencies developed among students through the offered study programs, mandatory subjects related to digital technologies, and forms of practical training related to Industry 5.0. Each of these three questions was a multiple-choice question. The clustering results, considering the institutional profile and type, are presented in Table 4.

The first cluster includes institutions with a highly advanced digital profile, where the development of students' technological competencies is comprehensive and well-balanced. Institutions in this group more frequently than others indicated the presence of competencies such as AI system design ($Project\_yes$, v-test = 8.60), cybersecurity ($Cyber\_yes$, v-test = 8.60), data analysis and Big Data ($Analysis\_yes$, v-test = 7.55), and programming skills ($Skills\_yes$, v-test = 6.19). At the same time, their educational programs included mandatory courses introducing artificial intelligence ($Intro\_yes$, v-test = 8.73), cloud technologies ($Tech\_yes$, v-test = 8.06), programming basics ($Basics\_yes$, v-test = 7.42), and data analysis methods ($Methods\_yes$, v-test = 6.04). These institutions also placed strong emphasis on practical training through computer labs using AI and Big Data ($Labs\_yes$, v-test = 8.36), group projects based on real-world data ($Projects\_yes$, v-test = 4.31), and internships in technology companies ($Internships\_yes$, v-test = 5.04). Moreover, there was a significant lack of responses indicating educational deficits, such as "no competencies" ($No\_competence\_no$, v-test = 5.69), "no classes" ($No\_classes\_no$, v-test = 5.91), and "no practical forms" (No_forms_no, v-test = 6.36). The profile of this cluster indicates institutions (mainly technical and economic) that are leaders in digitalization within the higher education sector.

The second cluster consists mainly of public institutions that also develop digital competencies, albeit in a less cohesive and systematic way than institutions in the first group. In this cluster, there was a clear overrepresentation of responses rejecting the absence of digital initiatives, as reflected in high v-test values: absence of "no competencies" declarations ($No\_competence\_no$, v-test = 7.94), "no classes" (v-test = 7.73), and "no practical forms" (v-test = 7.48). Institutions in this group more frequently offered group projects based on real-world data ($Projects\_yes$, v-test = 3.70) and reported developing programming skills ($Skills\_yes$, v-test = 3.18). This cluster was also linked to the institutional type – public institutions were dominant ($type$ = public, v-test = 5.55). At the same time, the intensity of some components in educational programs – such as cloud technologies or data analysis methods – was slightly lower, as confirmed by moderate v-test values for their absence ($Tech\_no$, v-test = 3.01; $Intro\_no$, v-test = 2.98). Institutions in this group (mainly vocational) can thus be characterized as moderately advanced in digital transformation, with clear potential for further development in this area.

The third cluster includes institutions that, to a significantly greater extent than others, declared a lack of digital competencies, a lack of courses related to digital technologies, and a lack of practical forms associated with Industry 5.0. This overrepresentation was strongly confirmed by high v-test values: lack of competencies ($No\_competence\_yes$, v-test = 12.64), lack of classes ($No\_classes\_yes$, v-test = 12.76), and lack of practical forms (No_forms_yes, v-test = 13.26). Additionally, this group showed significant overrepresentation of responses denying the presence of key curricular and practical components, such as programming basics ($Basics\_no$, v-test = 9.88), programming skills ($Skills\_no$, v-test = 9.49), data analysis ($Analysis\_no$, v-test = 9.34), data analysis methods ($Methods\_no$, v-test = 8.79), project work ($Projects\_no$,

Table 4. Competencies, subjects, and forms: Descriptions of the clusters by categories

Cluster	Cla/Mod	Mod/Cla	p-value	v-test
Cluster 1				
Intro = Intro_yes	73.1	77.6	<0.001	8.7
Project = Project_yes	93.3	57.1	<0.001	8.6
Cyber = Cyber_yes	58.4	91.8	<0.001	8.6
Labs = Labs_yes	65.6	81.6	<0.001	8.4
Tech = Tech_yes	78.0	65.3	<0.001	8.1
Analysis = Analysis_yes	52.4	89.8	<0.001	7.6
Basics = Basics_yes	50.0	91.8	<0.001	7.4
No_forms = No_forms_no	38.3	100.0	<0.001	6.4
Skills = Skills_yes	44.0	89.8	<0.001	6.2
Methods = Methods_yes	44.3	87.8	<0.001	6.0
No_classes = No_classes_no	36.6	100.0	<0.001	5.9
No_competence = No_competence_no	35.8	100.0	<0.001	5.7
Internships = Internships_yes	46.1	71.4	<0.001	5.0
Projects = Projects_yes	41.7	71.4	<0.001	4.3
institution = technical	40.3	51.0	0.003	3.0
institution = economic	52.9	18.4	0.016	2.4
Cluster 2				
No_competence = No_competence_no	57.7	100.0	<0.001	7.9
No_classes = No_classes_no	58.2	98.7	<0.001	7.7
No_forms = No_forms_no	59.4	96.2	<0.001	7.5
type = public	61.2	75.9	<0.001	5.6
Project = Project_no	49.0	97.5	<0.001	4.6
Projects = Projects_yes	57.1	60.8	<0.001	3.7
Skills = Skills_yes	53.0	67.1	0.001	3.2
Tech = Tech_no	47.9	88.6	0.003	3.0
Intro = Intro_no	48.9	83.5	0.003	3.0
Methods = Methods_yes	51.5	63.3	0.008	2.7
Internships = Internships_yes	53.9	51.9	0.008	2.7
institution = vocational	70.6	15.2	0.016	2.4
Labs = Labs_no	47.6	75.9	0.033	2.1
Basics = Basics_yes	50.0	57.0	0.041	2.0
Cluster 3				
No_forms = No_forms_yes	94.9	94.9	<0.001	13.3
No_classes = No_classes_yes	98.1	88.1	<0.001	12.8
No_competence = No_competence_yes	100.0	84.7	<0.001	12.6
Basics = Basics_no	60.8	100.0	<0.001	9.9
Skills = Skills_no	64.4	94.9	<0.001	9.5
Analytics = Analytics_no	57.3	100.0	<0.001	9.3
Projects = Projects_no	56.3	98.3	<0.001	8.8
Methods = Methods_no	61.1	93.2	<0.001	8.8
Internships = Internships_no	53.2	100.0	<0.001	8.6
type = private	57.3	86.4	<0.001	7.4
Cyber = Cyber_no	50.0	93.2	<0.001	6.9
Labs = Labs_no	45.2	96.6	<0.001	6.3
Intro = Intro_no	43.0	98.3	<0.001	6.0
Tech = Tech_no	40.4	100.0	<0.001	5.7
institution = pedagogical	78.3	30.5	<0.001	4.9
Project = Project_no	37.6	100.0	<0.001	4.6
institution = medical	70.0	23.7	<0.001	3.7

Note: Cla/Mod = distribution of significant categories across clusters; Mod/Cla = within-cluster distribution

v-test = 8.82), and internships ($Internships\_no$, v-test = 8.63). This cluster is also associated with institutional type – private institutions predominated ($type$ = private, v-test = 7.40), with pedagogical (v-test = 4.86) and medical profiles (v-test = 3.67) being the most frequent. The characteristics of this group point to a very low level of digital advancement and a lack of systemic solutions supporting the development of students' technological competencies. It can be regarded as a representation of institutions operating under a traditional educational model, largely overlooking the requirements and challenges related to digital transformation and the demands of Industry 5.0.

4.4. Needs and challenges of higher education institutions in adopting digital technologies

The final part of the analysis focused on the needs and challenges faced by higher education institutions in implementing digital technologies. The question regarding barriers was a multiple-choice question, whereas the question on institutional needs (support) asked respondents to indicate one primary form of support (single-choice question). The clustering results, taking into account the institutional profile and type, are presented in Table 5.

Table 5. Barriers and needs: Descriptions of the clusters by categories

Cluster	Cla/Mod	Mod/Cla	p-value	v-test
Cluster 1				
type = public	95.9	79.0	<0.001	10.2
No_interest = No_interest_no	79.3	93.3	<0.001	7.6
institution = technical	91.9	47.9	<0.001	6.0
institution = university	86.5	26.9	<0.001	3.3
No_need = No_need_no	66.5	98.3	0.002	3.0
support = financing	72.0	64.7	0.007	2.7
No_funds = No_funds_yes	69.6	79.0	0.007	2.7
institution = vocational	88.2	12.6	0.024	2.3
Cluster 2				
type = private	66.3	100.0	<0.001	10.7
No_interest = No_interest_yes	68.1	54.2	<0.001	6.0
institution = pedagogical	82.6	32.2	<0.001	5.3
institution = economic	88.2	25.4	<0.001	5.0
institution = medical	80.0	27.1	<0.001	4.6
Cluster 3				
support = no_need	100.0	100.0	<0.001	8.0
No_interest = No_interest_yes	14.9	77.8	0.001	3.3
No_funds = No_funds_no	13.5	77.8	0.002	3.1
No_infrastructure = No_infrastructure_no	10.0	88.9	0.006	2.8
No_need = No_need_yes	27.3	33.3	0.011	2.5
Low_competence = Low_competence_no	8.6	88.9	0.018	2.4

Note: Cla/Mod = distribution of significant categories across clusters; Mod/Cla = within-cluster distribution

The analysis of barriers to digital technology implementation and the support expected in adapting to Industry 5.0 principles led to the identification of three distinct classes of higher education institutions. Each class represents a different approach to digital transformation, reflected in both perceived obstacles and preferred forms of support.

The first cluster consists primarily of public institutions (v-test = 10.16), dominated by technical universities (v-test = 5.98) and general universities (v-test = 3.34). These institutions rarely cite a lack of student interest as a barrier ($No\_interest$ = no, v-test = 7.60) or a lack of need for implementing new solutions (No_need = no, v-test = 3.05), indicating a high level of awareness of the importance of digital transformation. Nevertheless, real challenges remain, particularly the lack of sufficient financial resources (No_funds = yes, v-test = 2.68), while the most frequently indicated form of support is funding for digital infrastructure ($support$ = financing, v-test = 2.70). The profile of this cluster suggests institutions that are structurally prepared to implement change but are constrained by external – primarily financial – factors.

The second cluster centers around private institutions (v-test = 10.65), including primarily pedagogical (v-test = 5.33), economic (v-test = 4.98), and medical universities (v-test = 4.64). A characteristic feature of this group is the above-average indication of lack of student interest as a significant barrier ($No\_interest$ = yes, v-test = 6.00), which may suggest a weaker feedback loop between the educational offer and students' expectations and needs. No clear preferences regarding support measures were identified in this group – these institutions rarely pointed to specific needs, which may indicate limited readiness or a lack of strategy for digital transformation. At the same time, the absence of significant responses indicating "no need for support" may be interpreted as a lack of a long-term development vision in the context of Industry 5.0.

The third cluster groups institutions that actively reject the need for support in implementing Industry 5.0 – all institutions in this class indicated “no need” as the dominant response ($support = no\_need$, v-test = 7.97). At the same time, the lack of perceived need for transformation itself appeared relatively frequently among the indicated barriers (No_need = yes, v-test = 2.53), along with a belief in the absence of technical infrastructure issues ($No\_infrastructure$ = no, v-test = 2.77), insufficient staff competencies ($Low\_competence$ = no, v-test = 2.36), or lack of funding (No_funds = no, v-test = 3.06). Nevertheless, some institutions in this class simultaneously reported a lack of student interest ($No\_interest$ = yes, v-test = 3.26), which may point to an inconsistency between the declared self-sufficiency and actual challenges in teaching. It can be assumed that institutions in this group do not identify the need for actively implementing Industry 5.0 solutions, which may stem from both limited awareness of the importance of these processes and their adopted organizational strategy.

5. Concluding remarks

The results of the study provide strong support for the main hypothesis (**H1**), confirming that the level of engagement in implementing Industry 5.0-related content, technologies, and practical components significantly varies depending on the institutional type and academic profile. Technical universities and public institutions were most likely to demonstrate organizational and programmatic readiness for digital transformation, including the use of AI, Big Data, and cloud technologies. In contrast, pedagogical, vocational, and artistic institutions, especially within the private sector, showed markedly lower levels of integration, often lacking dedicated units or specialized contents in educational programs. The availability of Industry 5.0-related specializations also differed substantially: while technical institutions offered such programs either partially or fully, pedagogical and medical universities predominantly reported no availability at all. These findings emphasize the systemic disparities in institutional readiness for Industry 5.0 and highlight the need for targeted support policies tailored to different types of institutions.

It is recommended that policymakers offer targeted funding and training to support less digitally advanced institutions. National strategies aligned with institutional needs and stronger academia-industry collaboration can accelerate and sustain AI integration in higher education.

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