Deliverable D2.1 - Report of the on-field analysis

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Executive Summary

Purpose and scope of the deliverable

This deliverable presents the consolidated results of the EduCATIA on-field analysis of AI-related educational gaps in higher education in Kazakhstan and Uzbekistan. Its purpose is to establish an evidence base for the modernisation of selected Bachelor's degree programmes and for the subsequent development of staff-training activities, educational materials, institutional guidance and practical pilots.

The deliverable combines several complementary analytical components. First, it presents the results of the EduCATIA questionnaires completed by students and academic staff. Second, it analyses the qualitative evidence collected through focus groups involving academics, institutional leaders, technical specialists and professional experts. Third, it examines the curricula selected by the partner institutions to determine whether AI-related knowledge, skills and responsibilities are already incorporated into programme outcomes, modules, teaching activities and assessment. Finally, it applies DigComp 3.0 as a European reference framework to translate the identified needs into a structured competence gap analysis and a set of Bachelor-level learning outcomes.

The four core programme analyses cover Philology and Language Teaching and Psychology in Uzbekistan, and Pharmacy and Medical and Preventive Medicine in Kazakhstan. These programmes represent education and pedagogy, psychological sciences, medicine, and biomedical sciences and public health. An additional analysis of IT Entrepreneurship at Astana IT University was undertaken because the programme was identified by the partner institution as a strategic priority for modernisation. Psychology and IT Entrepreneurship therefore extend the analytical scope beyond a narrow interpretation of Education and Health Sciences while responding directly to the priorities communicated by the partner universities and relevant ministries.

Taken together, the evidence shows that the central challenge is no longer the initial introduction of AI. AI is already widely used by students and teachers. The principal gap is the limited transformation of that use into explicit, critical, assessable, discipline-specific and institutionally governed competence.

Methods and evidence streams

The deliverable follows a mixed-method and cross-source approach.

The quantitative component consists of separate structured questionnaires for students and teachers. The final analytical dataset contains 3,717 student responses and 960 teacher responses, giving a combined sample of 4,677 respondents. The questionnaires examined frequency and purposes of AI use, self-perceived knowledge, previous training, institutional support, curriculum integration, competence transfer, ethical acceptance, educational effects, risk perception, accessibility and demand for further learning. The sample is voluntary and non-probability-based. It is strongly concentrated in Kazakhstan and Uzbekistan and cannot be treated as statistically representative of the complete national higher-education systems.

The qualitative component synthesises focus-group material from project institutions and partners in Kazakhstan, Uzbekistan, Italy and Germany. The available corpus includes transcripts, translations, participant profiles, edited thematic versions and analytical summaries. The groups represented higher-education teachers, researchers, institutional leaders, IT specialists and professionals working in medicine, public health, psychology, education, digital administration and applied AI. The analysis used recurring themes, contrasting positions and discipline-specific examples to explain and qualify the questionnaire results. Because the groups differed in composition and documentation quality, their findings are treated as informed qualitative evidence rather than representative national conclusions.

The curriculum component examines programme documentation, including programme descriptions, qualification requirements, curricula, module descriptions, programme learning outcomes, professional profiles, practical components and assessment information. AI-related provision was evaluated across technological foundations, applied AI, critical AI literacy, ethics and governance, discipline-specific applications and assessment. Absence from the available programme documentation is interpreted as lack of documented provision, not necessarily proof that the competence is absent from current teaching.

The DigComp component maps the student findings against the 21 competences of DigComp 3.0. The analysis treats Advanced proficiency as the appropriate general target for a Bachelor's graduate. It then translates the gaps into learning outcomes expressed through knowledge, skills and attitudes, together with observable evidence of attainment.

Achievement of the numerical Grant Agreement targets

The questionnaire target was substantially exceeded. The Grant Agreement requires an on-field analysis involving at least 100 Central Asian students, including 50 from Uzbekistan and 50 from Kazakhstan. The final dataset contains 1,938 students reporting Uzbekistan as their country of study and 1,587 reporting Kazakhstan. The required minimum was therefore exceeded in both countries. The additional 960 teacher responses considerably strengthen the evidence base, although teachers do not replace the required student sample.

The available documentation does not yet demonstrate achievement of all other numerical targets. The focus-group report identifies material from seven organising institutions or partners: Astana IT University, Kazakh National Medical University, Tashkent State Pedagogical University, Yangi Asr University, Sapienza University of Rome, Igor Vitale International and the University of Freiburg. It does not provide a consolidated record demonstrating ten distinct virtual focus groups and 60 unique participants. Some participant information is incomplete, and several sources are thematic summaries rather than complete transcripts. Consequently, the GA target of ten focus groups and 60 participants cannot be confirmed from the documents currently included. If additional sessions took place, a consolidated anonymised register should be added to demonstrate compliance.

Similarly, the supplied reports contain extensive bibliographies and numerous documentary, legal, institutional and empirical sources, but they do not provide a consolidated and deduplicated count demonstrating that at least 100 distinct sources were reviewed and analysed. This target may have been reached across the component reports, but it cannot be verified reliably without a consolidated source list or source-count statement.

The final merged document's compliance with the indicative length of approximately 120 pages should be checked after formatting and compilation. The required Kazakh, Italian and

Uzbek versions also need to be documented separately. The focus-group materials have been rendered into English, but the supplied files do not demonstrate that the complete final deliverable has been translated into all required languages.

There is also a minor denominator inconsistency in the questionnaire report: 3,717 students plus 960 teachers equals 4,677 respondents, while one passage states a total of 4,676. The final deliverable should consistently use 4,677 unless the master dataset establishes a different final denominator.

Main findings from the statistical analysis

The principal quantitative finding is widespread AI adoption combined with limited educational institutionalisation. AI was used at least occasionally by 92.4% of students and 92.9% of teachers. It was used often or always by 44.9% of students and approximately 48.3% of teachers. AI is therefore already part of routine academic activity.

Use is functionally diverse. Students most frequently reported AI-supported tutoring and explanations, translation, data analysis, accessibility functions and the production of study aids. Teachers used AI particularly for translation, presentations, assignment preparation, data analysis and improving the accessibility of lessons. These findings show that AI affects not only writing but also access to information, teaching design, data processing, study support and educational inclusion.

Frequent use does not correspond to advanced competence. Only 7.0% of students and 6.9% of teachers described their AI knowledge as advanced. Formal university training had reached 36.3% of students and approximately 49.4% of teachers. Only around one third of students reported general or field-specific AI teaching in their programme. The surveyed population therefore demonstrates substantial functional exposure but much more limited evidence of advanced, critical or professionally structured competence.

Demand for further learning is strong. Approximately 64.8% of students wanted additional AI competence relevant to their field. Among teachers, the corresponding proportion was 79.9%, while 81.2% wanted to learn more about AI in general. Demand is therefore not limited to beginners: it also exists among respondents who have already received some training.

An important discrepancy concerns competence transfer. While 64.1% of teachers reported transferring general AI competences and approximately 72% reported transferring field-specific competences, only 31.7% of students stated that they had learned AI skills from their professors. The questions were not identical and the respondents were not linked at course level, but the difference indicates that AI-related teaching may remain implicit, informal or insufficiently visible to students. Curriculum modernisation should therefore define explicit learning outcomes, activities and assessment criteria rather than relying on the demonstration of tools.

Assessment is the most sensitive area. Students and teachers were generally more accepting of AI as a support for producing materials than as a mechanism for evaluating competence. Only 48.9% of students considered AI-assisted assessment fair. Teachers expressed strong concern about reliability, critical thinking and academic integrity: 84.4% were concerned about the reliability of AI-generated information, 82.9% about possible effects on critical thinking and 79.5% about dishonest practices.

AI was also associated with educational benefits. A majority of students believed that it helped them learn faster or better, although teachers were more cautious. The findings support neither unrestricted technological optimism nor blanket prohibition. They show that educational value depends on task design, verification, transparency, teacher guidance and the preservation of student reasoning.

Accessibility constitutes an established opportunity. Accessibility-related AI uses were reported by 62.5% of students and 56.6% of teachers, while 63.0% of teachers stated that they used AI to make lessons more accessible to students with fewer opportunities. However, use alone does not establish that the tools are accurate, affordable, privacy-preserving or compatible with accessibility standards.

Institutional support remains uneven. Approximately 48% of both students and teachers recognised the existence of institutional AI guidance. The result indicates that around half of respondents either lacked such guidance or were unaware of it. Institutional differences were substantial, but country, institution and discipline are interconnected in the sample. The findings should therefore guide local needs assessment rather than be used to rank universities or countries.

Main focus-group findings

The focus groups confirm that AI adoption is broad but fragmented. Teachers, researchers and professionals already use AI for preparing materials, drafting documents, searching literature, analysing data, producing or translating code, developing assignments and supporting professional work. These practices are frequently based on individual experimentation rather than coordinated programme outcomes or approved institutional processes.

Verification was the most consistent competence gap. Participants described fabricated references, invented authors and identifiers, incorrect numerical claims, non-existent scientific structures, unsuitable clinical recommendations, generated code containing logical errors and assessment questions unrelated to the taught syllabus. The persuasive fluency of AI outputs was regarded as particularly dangerous because it can conceal error from users who lack sufficient disciplinary knowledge.

The discussions clarified that AI competence includes problem formulation, tool selection, prompting, iterative improvement, verification, contextualisation and the ability to decide not to use an output. Prompting alone is insufficient. A student or professional must understand the problem well enough to judge whether the response is relevant, reliable and appropriate to the local context.

Participants generally rejected both blanket prohibition and unrestricted use. The preferred approach was task-specific: some learning outcomes require unaided or closely supervised performance, while others can legitimately assess transparent and critical AI-supported work. Suggested assessment methods included oral defence, staged submissions, supervised practical work, portfolios, prompt and revision logs, reflective commentaries and comparison between assisted and unaided performance.

Human responsibility emerged as a common principle. AI may support teaching, grading, clinical reasoning, psychological assistance or professional analysis, but final consequential decisions should remain with appropriately qualified people. Human oversight must involve the genuine capacity to question, override and reject an automated recommendation, not merely formal approval of a result.

Privacy and data governance were recurrent concerns. Participants referred to personal, student, patient, research and institutional information being entered into external platforms without adequate understanding of storage, reuse or confidentiality. Institutions need approved-use cases, clear restrictions for sensitive information, suitable tools, transparent disclosure rules and identifiable responsibility for reviewing AI-supported decisions.

Faculty development was one of the strongest shared priorities. Teachers need more than introductory demonstrations of current products. They require practical and continuing support in verification, learning design, assessment, privacy, accessibility, discipline-specific applications and human oversight. Train-the-trainer capacity is necessary if improvements are to extend beyond the initial project participants.

The focus groups also showed that inclusion is conditional. AI can support translation, neurodivergent students, learners with disabilities and users requiring alternative formats. At the same time, it may introduce new barriers through subscription costs, limited language coverage, inaccurate simplification, inaccessible interfaces or the processing of sensitive disability-related data.

Principal curriculum gaps

Across the four core programmes, relevant digital, statistical or professional foundations already exist, but they do not yet form coherent AI competence pathways.

Philology and Language Teaching contains a compulsory Information Technologies module across the reviewed Yangi Asr tracks. The English curriculum also provides anchors in media literacy, educational technologies, materials development and foreign-language assessment. Nevertheless, AI foundations, natural-language processing, adaptive learning, automated feedback, AI-supported translation, learning analytics and corpus applications are not explicitly documented. Verification, bias, hallucinations, privacy, learner-data protection, disclosure and human responsibility are also absent. Provision is uneven across the English, Korean and Eastern Classical Languages tracks. A particularly important programme-specific issue is the need to use translation and text-generation tools without allowing them to replace vocabulary development, grammar, independent expression and interpretative judgement.

The Psychology programme has a strong classical foundation in general, experimental, developmental, social and clinical psychology, psychodiagnostics, counselling and psychological data processing. Its principal gaps extend beyond AI content. It lacks documented education in digital psychology, tele-psychological assistance, AI-supported assessment, automated interpretation, sensitive-data governance and professional deontology adapted to digital practice. It also requires stronger supervised practice, crisis and referral procedures, continuing professional development and train-the-trainer capacity. These gaps are especially important because AI adoption among psychology teachers is high, while formal training and competence transfer remain limited. Psychology must distinguish clearly between AI as an educational or research aid, AI as decision support and AI systems interacting directly with vulnerable clients.

Pharmacy has useful foundations in ICT, statistical methods, research, evidence-based medicine, pharmacy information technologies, modelling, automation and pharmacovigilance. However, no reviewed component explicitly covers AI, machine learning, generative AI or pharmacy-specific AI applications. Output verification, bias, uncertainty, hallucinations, privacy, health-data protection, disclosure and human oversight are not formalised. Modernisation should connect AI to medication safety, pharmacovigilance, drug-information work, pharmaceutical quality, production, hospital pharmacy, logistics and research while retaining pharmacist responsibility.

Medical and Preventive Medicine has a particularly strong basis in ICT, biostatistics, research methodology, epidemiology, public health, forecasting, GIS-oriented monitoring, risk assessment and professional practice. Its main weakness is the absence of explicit AI and machine-learning content and the lack of progression from conventional statistics to interpretable predictive analytics. Data quality, provenance, reproducibility, external validity, calibration, dataset shift, health-data governance and audit trails are not documented. These gaps affect population-level decisions concerning surveillance, outbreaks, environmental and occupational risks and resource planning.

The supplementary IT Entrepreneurship analysis presents a different profile. The programme already includes Python, machine learning, data mining, databases, information security, IT risk, IT governance, intellectual property and technological entrepreneurship. Its gap is therefore not basic exposure to AI. It lacks an explicit programme-wide competence progression, operational generative-AI skills, systematic output verification, AI-specific governance, documented human–AI collaboration, inclusive design and assessment rules for AI-supported work. Its technical and business foundations need to be connected to responsible innovation, procurement, lifecycle governance, transparency, human oversight and stakeholder communication.

Common modernisation priorities

The evidence supports a two-level curriculum model. All programmes need a common foundation in critical and responsible AI literacy, complemented by discipline-specific applications and safeguards.

The common foundation should cover basic understanding of AI systems, appropriate tool selection, problem formulation, prompting, source evaluation, hallucination and bias detection, data quality, privacy, academic integrity, copyright, transparent disclosure, human oversight, inclusion and the limits of automation.

Verification should become an explicit and assessed graduate competence. Students should demonstrate that they can trace claims, compare outputs with authoritative sources, identify error and bias, interpret uncertainty and justify whether an AI-supported result should be accepted, revised or rejected.

Assessment redesign is equally important. Programmes should distinguish among unaided tasks, supervised tasks and transparently AI-enabled tasks. Assessment should make reasoning visible through process documentation, error-detection exercises, oral defence, practical application and reflective justification. Automated AI detection should not serve as the sole evidence of misconduct.

Faculty development must accompany curricular change. Staff need differentiated pathways in foundational literacy, pedagogical integration, assessment, discipline-specific application and institutional leadership. Capacity building should be continuous, practice-oriented and supported by train-the-trainer arrangements.

Institutional governance must translate broad principles into operational rules. Universities need clear guidance on approved tools, sensitive data, disclosure, assessment, procurement, accessibility, human review, complaints and responsibility. Rules should explain responsible use rather than only list prohibitions.

Contribution to subsequent project activities

The results provide a direct basis for the next stages of EduCATIA. Programme teams can use the findings to revise graduate outcomes, map existing modules, identify suitable integration points and select discipline-specific cases. The DigComp-based learning outcomes provide a common competence language while allowing programme-specific weighting.

Capacity-building activities should be organised around the confirmed gaps: verification, assessment design, privacy, data governance, responsible professional application and institutional implementation. Training should use cases from language teaching, psychology, pharmacy, epidemiology, public health and AI-enabled entrepreneurship.

Educational materials should include reusable explanations, verification protocols, privacy and risk-assessment exercises, discipline-specific case studies, model assessment rubrics, AI-use declarations, prompt and revision logs, oral-defence guidance and examples of justified rejection of AI outputs. Materials should be accessible, multilingual and adaptable to changing tools.

Pilots should begin with bounded, supervised and evaluable activities using approved tools and appropriately governed, anonymised or synthetic data. Evaluation should measure competence and educational quality rather than merely frequency of tool use. Repeated DigComp-aligned assessment can establish whether students progress from Basic or Intermediate functional use towards Advanced, critical and professionally responsible competence.

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Report on the EduCATIA questionnaires

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1. General introduction to the research

1.1. Context and framework of the EduCATIA project

This research was conducted within the framework of the Erasmus+ Capacity Building in Higher Education project **EduCATIA – Advanced Training in Artificial Intelligence Technologies for Kazakhstan and Uzbekistan**. The project responds to the rapid expansion of artificial intelligence and its growing influence on university teaching, research, professional practice and the digital transformation of higher education institutions.

EduCATIA is based on the recognition that the integration of artificial intelligence into universities cannot be limited to the introduction of new technological tools or isolated technical content. It also requires the development of pedagogical and professional competences, the strengthening of teaching capacity, the modernisation of curricula, the definition of ethical criteria and the establishment of institutional frameworks to guide its use. It further requires more structured cooperation among universities, public authorities, professional organisations and relevant economic sectors.

In this context, the project focuses primarily on the higher education systems of Kazakhstan and Uzbekistan, promoting the transfer and critical adaptation of European experience and reference frameworks. Its overall purpose is to support higher education institutions in both countries in integrating artificial intelligence in a systematic, sustainable and inclusive manner that is appropriate to their respective academic and professional contexts. The project combines curriculum modernisation, teacher training, institutional reform, international mobility, university–industry cooperation and the development of practical experience relating to applications of artificial intelligence.

The intervention is structured around four main academic areas:

1. Education and pedagogy.
2. Medicine.
3. Biomedical sciences and public health.
4. Psychological sciences and cognitive research.

These areas are considered separately because the applications, risks and competences associated with artificial intelligence are not equivalent across all disciplines. In education, for example, adaptive learning, assessment, learning analytics and teacher training are particularly relevant. In medicine and biomedical sciences, patient safety, data quality, explainability and professional oversight are central concerns. In public health, particular attention must be paid to epidemiological analysis, disease surveillance and resource management. In psychology and cognitive research, privacy, bias, the limitations of automated assessment and the protection of people in vulnerable situations are especially important.

1.2. Scope of the research

The research analyses the current role of artificial intelligence within the participating higher education institutions, drawing on the experiences, practices, knowledge, attitudes and needs reported by two central groups within the academic community: students and teaching staff.

The study is not limited to determining whether respondents use artificial intelligence tools. Its scope is broader: it examines the extent to which this use is accompanied by sufficiently developed competences, specific training, teacher guidance, institutional support, ethical criteria and recognisable integration into study programmes.

The research therefore addresses the potential gap between the widespread practical use of artificial intelligence and its educational institutionalisation. This distinction is fundamental, since the frequent use of generative tools, translation systems, writing assistants or data-analysis applications does not necessarily mean that students and teachers are able to evaluate their outputs critically, detect errors or bias, protect personal data, disclose their use or apply them appropriately within their professional fields.

Among other dimensions, the questionnaires examine specific uses of artificial intelligence, frequency of use, self-perceived knowledge, training received, the existence and clarity of institutional guidance, the transfer of competences between teachers and students, ethical acceptance, perceived usefulness, risk perception, accessibility and the demand for AI-supported university services and resources.

1.3. Aim and objectives of the study

The main aim of the research is to provide an empirical basis for decision-making within the EduCATIA project. The results are intended to ensure that future activities relating to curriculum development, teacher training, the production of educational resources, policy formulation and cooperation with the professional sector respond to observed needs rather than solely to general assumptions about the digitalisation of higher education.

More specifically, the research seeks to:

- describe how frequently and for what purposes students and teachers use artificial intelligence in their academic activities;
- analyse their levels of self-perceived knowledge and their previous training experience;
- assess the level of institutional support and preparedness within the participating universities;
- identify general and discipline-specific training needs;
- examine how AI-related competences are transferred from teachers to students;
- investigate attitudes towards the use of artificial intelligence in teaching, learning, the production of educational materials and assessment;
- identify concerns relating to reliability, critical thinking, academic integrity, privacy and the potential substitution of human functions;
- analyse the potential of artificial intelligence to improve accessibility, inclusion and support for students with fewer opportunities;
- obtain evidence to inform the design of training modules, institutional guidelines, pilot initiatives, tutoring systems and university–industry cooperation mechanisms.

These objectives correspond to the project’s three main strategic directions: integrating artificial intelligence into higher education policies; modernising curricula and strengthening teaching capacity; and promoting innovation and cooperation with the professional sector.

1.4. General methodological approach

For analytical purposes, the research takes the form of a quantitative, descriptive and cross-sectional study based on structured questionnaires administered separately to students and teachers from the participating institutions. The two instruments cover a number of common thematic areas, making it possible to examine converging tendencies and differences between the two groups. However, their questions should not automatically be treated as equivalent, since the meaning of using, teaching, transferring or assessing AI competences varies according to the respondent's academic role.

The analysis is based primarily on the final dataset, while the tables prepared separately for students and teachers are used for verification purposes. It considers overall distributions and, where the composition of the sample permits, differences by country, university, academic field and other relevant characteristics.

The analysis distinguishes between single-response and multiple-response questions, between percentages calculated on the basis of the entire sample and percentages calculated on the basis of valid responses, and between the absence of a particular characteristic and the absence of a response. The procedures used for data cleaning, recoding, denominator selection, the treatment of missing data and the identification of possible anomalies are presented in detail in the methodology section of the report.

The information collected is primarily self-reported. The results therefore reflect the experiences, perceptions and assessments of the participants, but they do not constitute an objective measurement of their technical competence and do not allow causal relationships to be established. These findings will subsequently be complemented by an analysis of the focus groups and by a structured review of the degree programmes selected for modernisation by the partner universities. The questionnaire analysis initially identifies needs at the level of broad academic areas; the later curriculum review will examine the actual modules, learning outcomes, assessment methods and professional requirements of each selected programme in order to formulate programme-specific recommendations. Similarly, comparisons between countries or institutions must be interpreted in the light of the unequal distribution of the sample, the small size of certain subgroups and the possible influence of linguistic, institutional and disciplinary factors.

1.5. Role of the research within EduCATIA

The research performs both a diagnostic and a strategic function within the project. It does not merely seek to assess the acceptance of artificial intelligence, but to determine which capacities need to be developed in order to transform individual and fragmented practices into consolidated academic, professional and institutional competences.

In this respect, the results are intended to support:

- the review of curricula and the integration of artificial intelligence content into study programmes;
- the design of differentiated teacher-training pathways;
- the formulation of observable learning outcomes for students;

- the development of guidance on academic integrity, transparency, data protection and human oversight;
- the redesign of assessment strategies;
- the development of discipline-specific applications;
- the creation of open educational resources;
- the implementation of inclusive and accessible initiatives;
- the strengthening of internships, mentoring and cooperation with external organisations.

The adopted perspective does not assume that increased use of artificial intelligence will automatically produce better educational outcomes. The value of these technologies depends on the pedagogical, ethical, institutional and disciplinary conditions under which they are used. For this reason, the report jointly analyses practical use, competence maturity, institutional preparedness, ethical acceptance, risk perception and training needs.

In conclusion, the research provides EduCATIA with an empirical basis for moving from the spontaneous adoption of individual tools towards a more critical, explicit and responsible form of educational integration. Its principal contribution is to identify not only the extent to which artificial intelligence is being used, but also which competences are lacking, what institutional support is required and which conditions must be established for its integration to contribute effectively to the quality, inclusion and sustainability of higher education in Kazakhstan and Uzbekistan.

2. Methodology

2.1. General research design

The component analysed in this report follows a **quantitative, descriptive and cross-sectional design**, based on two structured questionnaires addressed respectively to students and teachers from the institutions participating in EduCATIA.

The questionnaires were designed to collect information on the academic use of artificial intelligence, self-perceived knowledge, training received, institutional support, ethical attitudes, perceived usefulness and risk, and needs relating to training and curriculum development.

The two populations were analysed separately. Although the instruments share several thematic dimensions, the questions are not fully equivalent. In particular, the student questionnaire focuses on learning experiences, support received and desired university services, whereas the teacher questionnaire also examines teaching design, competence transfer, accessibility, assessment and perceived professional risks.

For this reason, comparisons between students and teachers were made only where the content and meaning of the questions were sufficiently similar. Two questions were not considered comparable merely because they addressed the same general topic.

The research is based on a voluntary institutional sample. The available files do not contain a sampling frame or known probabilities of selection; the sample must therefore be regarded as **non-probability-based**. Consequently, the findings describe the individuals who completed the questionnaires but should not be interpreted as statistically representative estimates of the entire university populations of Kazakhstan, Uzbekistan or the participating European countries.

2.2. Data collection

Two separate questionnaires were administered:

- a questionnaire for students;
- a questionnaire for teaching staff.

The structure of the exported files, the presence of timestamps and the existence of different language versions indicate that the questionnaires were completed electronically and were self-administered. However, the analytical files do not make it possible to establish with complete certainty the platform used, the official opening and closing dates, the distribution channels or the total number of people invited to participate. These details should be verified with the institutions responsible for administering the survey before the final version of the report is completed.

Participation was individual, and responses were not linked to any objective competence test. At the end of the questionnaires, respondents were presented with a statement concerning the project's privacy policy and an optional field through which they could request further information about the research findings and EduCATIA activities.

The questionnaires were distributed in several languages in order to facilitate participation across different national and institutional contexts. In the case of students, the files identify responses from versions in English, German, Italian, Kazakh, Russian and Uzbek. Responses in Italian were collected through two institutional versions corresponding to Sapienza University of Rome and Igor Vitale International.

Distribution of responses by questionnaire language

Questionnaire language	Students, n	Students, %	Teachers, n	Teachers, %
English	378	10.2	23	2.4
German	1	<0.1	1	<0.1
Italian	90	2.4	22	2.3
Kazakh	699	18.8	126	13.1
Russian	1,280	34.4	604	63.0
Uzbek	1,268	34.1	184	19.2
Total	**3,717**	**100.0**	960	**100.0**

The language versions were harmonised through a common structure of variables and response categories. Nevertheless, the use of different languages may have influenced the interpretation of certain terms, particularly concepts such as competence, fairness, clarity of guidelines, critical thinking and accessibility. Questionnaire language should therefore be considered a potential source of variation rather than merely a technical characteristic of the data collection process.

2.3. Data preparation and cleaning

The final dataset was obtained through standard data-cleaning procedures aimed at correcting obvious response-format inconsistencies and harmonising the data. These procedures included, for example, standardising birth-year entries when respondents did not follow the questionnaire instructions (e.g. entering month and year or two-digit years instead of a four-digit birth year), correcting evident coding inconsistencies and removing spreadsheet summary rows. No systematic exclusion of respondent records was performed as part of these procedures.

Initial records and analytical sample

Population	Records in the final dataset
Students	3,717
Teachers	960
Total	**4,677**

The report uses **DATASET FINAL REV_7b_grafici.xlsx** as its primary reference file. This dataset contains 3,717 student records and 960 teacher records. The separate tables prepared for students and teachers were used as verification tools and to reconstruct the analytical criteria applied.

The main data-cleaning procedures identifiable in the files were as follows:

1. **Harmonisation of language versions.**

Questions administered in different languages were transferred into a common variable structure while preserving comparable response categories.

2. **Standardisation of labels.**

Spelling variants, additional spaces, capitalisation and different forms of the same institutional or categorical label were harmonised. For example, the two recorded forms of Tashkent State Pedagogical University were combined into a single institutional category.

3. **Recoding of responses.**

Binary responses were standardised as “Yes” and “No”, while ordinal scales were coded using ordered categories. The letters used internally in the dataset function as response codes and should not be treated as numerical scores in themselves.

4. **Control of birth years and enrolment years.**

Plausible values were grouped into ranges. Missing, incomplete or clearly anomalous values were classified as unavailable or placed in a residual category. For students, the year of first university enrolment was also grouped into intervals.

5. **Classification of teaching disciplines.**

In addition to the faculty selected from closed categories, teachers reported the subject they taught through an open-ended response. In the analytical tables, these responses were subsequently classified into broader disciplinary areas:

a. Biological and Natural Sciences;

b. Computer Science and ICT;

c. Economics, Business and Tourism;

d. Education, Psychology and Social Sciences;

e. Humanities, Law and Arts;

f. Languages and Literature;

g. Mathematics, Statistics and Physical Sciences;

h. Medicine and Health Sciences;

i. Other or Multidisciplinary;

j. information not available.

This classification makes it possible to analyse the diversity of subjects taught, but it should not be confused with either the six closed faculty categories or the four priority academic areas of the EduCATIA project. Any subsequent grouping into the four project areas should explicitly document which disciplines are assigned to each category.

No exact duplicates were identified when all fields in the final records were considered jointly. The existence of identical response profiles across some closed questions was not considered, in itself, evidence of duplication, since different respondents may legitimately select the same combination of answers.

2.4. Composition of the analysed sample

The final sample consists of **4,676 participants**: 3,717 students and 960 teachers.

Distribution by self-reported country of study/activity

Country	Students, n	Students, %	Teachers, n	Teachers, %
Germany	39	1.0	1	0.1
Italy	104	2.8	19	2.0
Kazakhstan	1,587	42.7	679	70.7
Uzbekistan	1,938	52.1	249	25.9
Other country	49	1.3	12	1.3
Total	**3,717**	**100.0**	**960**	**100.0**

Note: Country and university were collected through separate self-reported questions. The figures should therefore not be interpreted as directly equivalent measures of national or institutional affiliation.

The sample is strongly concentrated in Kazakhstan and Uzbekistan. Together, the two countries account for 94.8% of the student sample and 96.6% of the teacher sample. The responses collected in Italy and Germany were retained in order to document all valid participation from the project institutions and to provide limited contextual information. They were not designed as a representative or matched European control group.

The role of the European partners within EduCATIA should therefore be distinguished from the role of the survey sample. European experience, competence frameworks and institutional practices provide reference points for curriculum development and capacity transfer, but the questionnaire data do not provide an empirical basis for claiming that European higher education systems perform better than those of Kazakhstan or Uzbekistan. The Italian sample is small and institutionally and disciplinarily heterogeneous, while the German student records contain substantial inconsistencies between reported country and university. Balanced Europe–Central Asia comparisons are consequently not supported by the available data.

Distribution by university

University	**Students, n**	**Students, %**	**Teachers, n**	**Teachers, %**
Asfendiyarov Kazakh National Medical University	1,025	27.6	592	61.7
Astana IT University	148	4.0	13	1.4
Sapienza University of Rome	60	1.6	12	1.3
Tashkent State Pedagogical University	1,460	39.3	200	20.8
University of Freiburg	13	0.3	1	0.2
Yangi Asr University	194	5.2	43	4.5
Other institutions	817	22.0	98	10.2
Total	**3,717**	**100.0**	**960**	**100.0**

The institutional distribution is also uneven. Tashkent State Pedagogical University and Asfendiyarov Kazakh National Medical University together account for 66.9% of the student sample. Among teachers, Asfendiyarov Kazakh National Medical University alone represents 61.7% of the sample.

Differences observed between countries may therefore partly reflect the institutional composition of the sample. Country and university should not be treated as fully independent factors.

The country and university variables were collected through separate self-reported questions and should not be interpreted as equivalent indicators of institutional or national affiliation.

Source: EduCATIA final survey dataset, students, questions 1–2, valid N = 3,717.

Distribution by gender

Gender	Students, n	Students, %	Teachers, n	Teachers, %
Male	910	24.5	214	22.3
Female	2,735	73.6	739	77.0
Prefer not to say	72	1.9	7	0.7
Total	**3,717**	**100.0**	**960**	**100.0**

Women represent approximately three quarters of both populations. This distribution should be taken into account in any analysis by gender, since the group sizes are markedly unequal.

Distribution by declared academic area

Academic area	Students, n	Students, %	Teachers, n	Teachers, %
Biomedical sciences	51	1.4	26	2.7
Medicine	1,469	39.5	553	57.7
Computer science	93	2.5	12	1.3
Psychology	68	1.8	46	4.8
Education	1,291	34.7	109	11.4
Other areas	745	20.0	214	22.3
Total	**3,717**	**100.0**	**960**	**100.0**

The student sample is particularly concentrated in medicine and education, while more than half of the teachers report teaching in medicine. The samples for biomedical sciences, computer science and psychology are considerably smaller. Disciplinary results should therefore always be presented together with the size of each subgroup, and substantive importance should not be attributed to differences based on very small numbers of respondents.

The questionnaire categories do not correspond exactly to the four academic areas defined by EduCATIA. In particular, computer science and “other areas” appear as separate categories. They should not be redistributed across the four project areas without first establishing explicit and verifiable classification rules.

2.5. Structure of the student questionnaire

The student questionnaire contains **45 numbered questions**. Its structure can be organised into the following sections.

Section 1. Academic and sociodemographic profile: questions 1–6

This section collects information on:

- university;
- country;

- gender;
- year of birth;
- field of study;
- year of first university enrolment.

The year of birth and year of first enrolment were subsequently grouped into ranges in order to facilitate analysis and reduce the influence of anomalous values.

Section 2. Practical use of artificial intelligence: questions 7–15

This section examines:

- general frequency of AI use for study purposes;
- text translation;
- tutoring, explanations and study support;
- accessibility;
- report writing;
- the creation of mind maps, charts and study materials;
- data analysis;
- other uses;
- the AI-related task in which the student considers themselves most competent.

General frequency was measured using four ordered categories: never, sometimes, often and always.

Specific uses were recorded through independent binary variables. Although these questions form a battery of multiple possible uses, they do not constitute a single multiple-choice question. Each participant could answer affirmatively to several uses. Consequently, the sum of the percentages for questions 8–14 may exceed 100%.

The question concerning the task in which the respondent considers themselves most competent is, by contrast, a single-response item.

Section 3. AI maturity and interest: questions 16–20

This section includes:

- number of tools used;
- use of paid tools;
- self-perceived level of knowledge;
- interest in learning more about AI in general;
- interest in acquiring AI competences related to the respondent’s field of study.

The number of tools used and self-perceived knowledge were measured using ordinal categories. Self-perceived knowledge was classified as none, basic, intermediate or advanced.

Interest in learning was measured using a four-point scale without a neutral category:

- strongly disagree;

- partly disagree;
- mostly agree;
- strongly agree.

Section 4. Training and institutional support: questions 21–25 and 29–33

This section examines:

- participation in training activities during the previous two years;
- the existence of university guidelines;
- the clarity of those guidelines;
- the provision of general and discipline-specific competences;
- students' perceptions of teachers' use of AI;
- the acquisition of AI competences through teachers;
- the presence of general and field-specific AI teaching within the study programme;
- satisfaction with the use of AI within the degree programme.

The clarity of institutional guidelines was measured using five categories: very unclear, unclear, clear, very clear and no guidelines. The "no guidelines" category should not be interpreted as the lowest point on a clarity scale, since it represents a conceptually different condition.

Section 5. Ethical acceptance and demand for services: questions 26–28 and 34–37

This section examines:

- acceptance of AI use for completing assignments;
- acceptance of teachers' use of AI to assess competences;
- acceptance of teachers' use of AI to create materials;
- interest in an AI tutor for administrative procedures;
- interest in an AI tutor during internships;
- interest in an AI tool for initial psychological support;
- interest in studying through AI-generated lessons.

These questions use binary response categories. The results indicate declared acceptance or demand but do not establish the specific conditions under which each respondent would consider the service acceptable.

Section 6. Usefulness, risks and institutional priorities: questions 38–43

This section includes perceptions relating to:

- faster learning;
- improved learning;
- reduced critical thinking;
- improvement in the quality of teaching and learning;
- the need to increase the number of AI courses in the respondent's field;
- the need to improve teachers' competences.

The questions were answered using a four-point ordinal scale without a neutral option.

Section 7. Follow-up and privacy: questions 44–45

The final two questions concern:

- the possibility of receiving information about the results and the project;
- acceptance of the privacy policy.

The follow-up field contains an email address in many cases and should be kept separate from the dataset used for substantive analysis. It was not used as an explanatory variable.

2.6. Structure of the teacher questionnaire

The teacher questionnaire contains **42 numbered questions**.

Section 1. Professional and sociodemographic profile: questions 1–6

This section includes:

- university;
- country of teaching activity;
- gender;
- year of birth;
- faculty;
- subject taught.

The subject taught was collected through an open-ended response and was subsequently classified into broader disciplinary areas.

Section 2. Use of AI in teaching: questions 7–15

This section examines:

- general frequency of AI use in teaching;
- translation;
- creation of presentations;
- accessibility;
- report writing;
- mind maps, charts and teaching resources;
- data analysis;
- creation of assignments;
- other uses.

General frequency was measured using a four-category scale. Specific uses were recorded as independent binary variables and their percentages should therefore not be summed.

Section 3. AI maturity and interest: questions 16–20

This section includes:

- number of tools used;

- use of paid tools;
- self-perceived knowledge;
- interest in learning more about AI;
- interest in developing AI competences related to the respondent's own teaching field.

Section 4. Training, institutional support and competence transfer: questions 21–26

This section examines:

- participation in training activities organised by the university;
- the existence and clarity of institutional guidelines;
- the transfer of general AI competences to students;
- the transfer of field-specific AI competences;
- the use of AI to improve accessibility for students with fewer opportunities.

This section makes it possible to analyse not only the support received by teachers but also the extent to which this support is transformed into competences transferred to students.

Section 5. Ethical acceptance and satisfaction: questions 27–30

This section includes:

- acceptance of AI use for creating teaching content;
- acceptance of AI use for assessing competences;
- acceptance of students' use of AI;
- satisfaction with the respondent's own use of AI in teaching.

Section 6. Educational usefulness and institutional priorities: questions 31–36

This section examines:

- faster learning;
- improved learning;
- possible reduction in critical thinking;
- overall improvement in the quality of teaching and learning;
- the need to increase the number of AI courses;
- the need to improve teachers' competences.

Section 7. Risk perception: questions 37–40

This section collects information on concerns relating to:

- dishonest practices;
- effects on critical thinking;
- possible replacement of teachers;
- reliability of AI-generated information.

The questions on dishonest practices and critical thinking were recorded as binary responses, whereas the possible replacement of teachers and reliability were measured using four-point ordinal scales. This difference in response format must be taken into account when comparing risk indicators.

Section 8. Follow-up and privacy: questions 41–42

The final questions concern the possibility of receiving information about the project and acceptance of the privacy policy. Contact details do not form part of the substantive analysis.

2.7. Analytical strategy

The analysis was conducted mainly through frequency distributions, percentages and contingency tables.

For each question, the following were calculated where relevant:

- number of responses in each category;
- percentage of valid responses;
- size of the population analysed;
- number of missing responses;
- distribution within each university, country or group;
- composition of each response category.

The tables prepared by Simona Perone contain two types of percentages:

1. **Row percentages or within-group percentages.**

These indicate the proportion of a given country, university, gender or academic area selecting a particular response. They are the most appropriate percentages for comparing groups of different sizes.

2. Column percentages.

These indicate the proportion of all respondents selecting a particular answer who belong to each group. They describe the composition of a response category but are strongly influenced by the unequal sizes of universities and countries.

Substantive comparisons in the report should therefore be based primarily on within-group percentages. Column percentages may be used to describe the origin of responses but should not be used to conclude that a given group has a higher prevalence of a particular attitude or behaviour.

For four-point scales, results may be presented using the four original categories or grouped into two broader categories:

- disagreement: strongly or partly disagree;
- agreement: mostly or strongly agree.

Whenever this aggregation is used, it should be stated explicitly. For negatively worded questions, agreement does not indicate a positive evaluation of AI but rather a higher perception of risk or negative impact.

Percentages should be calculated on the basis of valid responses to each question. Where there are no missing values, the valid N corresponds to the total sample size. Where responses are missing, both the valid N and the number of missing responses should be reported.

To avoid imposing substantive meaning through unspecified cut-off points, percentages are generally reported numerically and interpreted in relation to the wording of each question, the response scale and the relevant comparison group. For binary questions, values between 45% and 55% are described as indicating an approximately even division or no clear predominance. Values above 50% may be described as a numerical majority, but the terms "clear majority" and "large majority" are reserved, respectively, for proportions of at least 60% and 75%. The terms "higher" and "lower" refer to comparisons between groups or indicators and do not, by themselves, denote an absolute level. These thresholds are descriptive conventions rather than tests of statistical or practical significance.

No weighting was applied to correct for the uneven distribution of the sample. Most comparisons are descriptive and are interpreted in relation to group size, effect magnitude and substantive relevance. Limited inferential tests were conducted for selected comparisons explicitly discussed in the report. Chi-square tests of independence were used for associations between categorical variables, accompanied by Cramér's V as a measure of effect size. For subgroup analyses involving more than two categories, significant omnibus tests were followed by pairwise comparisons with Holm adjustment. Associations involving ordered age groups and ordinal response scales were assessed using Spearman's rank correlation. Categories with very small samples were retained for descriptive purposes but excluded from confirmatory subgroup tests where stable inference could not be supported.

Where several related tests were performed, adjustment for multiple comparisons was considered. Because the survey was based on a voluntary, non-probability sample, statistical tests are used to assess the strength of associations within the analytical sample and not to generalise the findings to national university populations.

Possible composite indices of use, maturity, institutional support, ethical acceptance and risk perception represent an additional line of analysis. They should not be presented as established results until their component variables, coding, direction, treatment of missing values, weighting and internal consistency have been documented.

2.8. Data preparation and quality control

The final dataset was obtained through standard data-cleaning procedures aimed at ensuring consistency and harmonising the responses prior to analysis. These procedures focused on correcting obvious response-format inconsistencies and resolving coding issues that could be objectively identified from the questionnaire data.

Examples of these procedures included the standardisation of variables where respondents had not followed the questionnaire instructions (e.g. entering the year of birth using formats other than the requested four-digit year), the harmonisation of categorical coding, and the correction of a small number of evident institutional coding inconsistencies. Where the available information did not allow an objective correction, the original responses were retained.

The cleaning process also included the removal of spreadsheet subtotal and summary rows generated during intermediate processing, which are not respondent records and therefore do not affect the analytical dataset.

As agreed by the project partners during the survey design, respondents were generally not required to authenticate using their institutional email addresses. While this decision was intended to facilitate participation, it also meant that, in many cases, individual respondents could not be re-contacted to clarify ambiguous or inconsistent answers. Consequently, only corrections that could be objectively justified from the information contained in the questionnaire itself were performed, while responses that could not be verified with certainty were retained in their original form.

No substantive modifications were made to respondents' answers beyond these technical harmonisation procedures. The analyses presented in this report are based on the final cleaned dataset used for all descriptive statistics.

2.9. Methodological limitations

The findings should be interpreted in the light of the following limitations:

- the sample is voluntary and non-probability-based;
- the total number of people invited to participate and the response rate are not available;
- respondents are strongly concentrated in particular universities and countries;
- some European and disciplinary subgroups are very small;
- the European respondents, due to the difference in target audience, do not constitute a matched or representative comparison group and cannot be used to test a general hypothesis of European institutional advantage;
- responses reflect self-reported perceptions and competences;
- the cross-sectional design does not allow causal relationships to be established;
- different language versions may have introduced variations in interpretation;
- country, university and academic area are partially interrelated;
- some open-ended or anomalous variables required manual classification;
- student and teacher questions are not always directly equivalent;
- the absence of a neutral point in some scales may have encouraged respondents to express either agreement or disagreement;
- the rapid evolution of AI technologies means that the results describe the situation during the data-collection period rather than a permanent condition.

These limitations do not invalidate the diagnostic value of the research, but they define the type of conclusions that may reasonably be drawn. The data make it possible to identify patterns, needs and priority areas for intervention within EduCATIA, but they do not allow the precise prevalence of these characteristics to be estimated across the entire national higher education systems.

3. Results

This section presents the main findings emerging from the EduCATIA questionnaires administered to students and teachers. The analysis combines the overall results obtained from the final dataset with the more detailed breakdowns developed separately for the two respondent groups.

The purpose of this section is not merely to describe the frequency of individual responses, but to identify broader patterns relating to AI use, competence maturity, training, institutional support, ethical acceptance, perceived usefulness, risk perception, accessibility and curriculum needs. Particular attention is paid to the relationship between the widespread practical use of artificial intelligence and the extent to which that use is supported by formal training, explicit learning outcomes, institutional guidance and discipline-specific integration.

Student and teacher results are presented separately before the most relevant similarities and differences between the two groups are considered. Comparisons are made only where the wording and meaning of the questions are sufficiently comparable. Where appropriate, the analysis also considers differences by country, university, academic area, gender, questionnaire language and other relevant characteristics.

The final dataset is used as the primary source for all numerical findings, while the separate student and teacher tables are used to verify calculations and provide more detailed disaggregated analysis. Percentages are calculated on the basis of valid responses unless otherwise stated. For multiple-use batteries, respondents could select more than one option; consequently, the corresponding percentages should not be added together.

The findings must be interpreted in the light of the unequal distribution of the sample. Respondents are strongly concentrated in Kazakhstan and Uzbekistan and in a limited number of partner universities, while some national, institutional and disciplinary subgroups are comparatively small. Differences between groups are therefore interpreted descriptively and are not treated as representative estimates of the wider national higher education systems.

The results are organised around the following analytical dimensions:

- practical use of artificial intelligence;
- self-perceived knowledge and AI maturity;
- training received and demand for further training;
- institutional support and readiness;
- transfer of AI competences;
- ethical acceptance;
- perceived usefulness;
- risk perception;
- inclusion and accessibility;
- demand for AI-supported university services;
- disciplinary and curricular needs.

Taken together, these dimensions make it possible to assess not only the extent to which artificial intelligence is already being used, but also the degree to which this use has been transformed into explicit, critical, ethical and institutionally supported educational practice.

3.1. Overview of the main findings

3.1.1. Central finding: widespread adoption but limited institutionalisation

The central finding of the survey is the existence of a gap between the widespread practical use of artificial intelligence and its still limited educational and institutional integration.

AI is already used by a large majority of both students and teachers. Only 7.6% of students reported never using AI for study purposes, while 44.9% used it often or always. Similarly, only 7.1% of teachers reported never using AI in their teaching, and 48.4% used it often or always. Overall, 92.4% of students and 92.9% of teachers therefore used AI at least occasionally.

These figures indicate that AI is no longer a marginal or experimental technology within the surveyed academic communities. It is already embedded in a broad range of study and teaching practices. However, the results also show that this practical diffusion has not yet been matched by an equivalent level of formal training, curricular integration, institutional guidance or advanced competence.

Among students, only 36.3% had attended AI-related training activities at their university during the previous two years. Approximately one third reported that their degree programme included general AI teaching (34.9%) or field-specific AI teaching (34.0%). Among teachers, 49.3% had participated in university-organised AI training, while 48.9% reported that their university provided guidelines on the use of AI by teaching staff.

The overall pattern suggests that AI is entering higher education to a considerable extent through individual initiative and informal experimentation rather than through a fully developed and coherent institutional strategy.

Table 3.1. Selected indicators of AI adoption and institutionalisation

Indicator	Students, %	Teachers, %
Use AI often or always	44.9	48.3
Never use AI	7.6	7.1
Describe their AI knowledge as advanced	7.0	6.9
Use paid AI tools	21.5	27.4
Participated in university AI training	36.3	49.4
Report that institutional AI guidelines exist	48.0	48.9
Agree that they would like to learn more about AI in their field	64.8	79.9

Population: students, valid N = 3,717; teachers, valid N = 960.

Note: Student and teacher questions refer to similar dimensions but are not always identically worded. Comparisons should therefore be interpreted as contrasts between related indicators rather than as measurements based on fully equivalent items.

3.1.2. AI use is broad and functionally diverse

The use of AI extends well beyond a single application or general-purpose chatbot. Students reported using it for a variety of academic activities. The most common uses were tutoring, explanations and study support (78.7%), translation (75.1%), data analysis (69.7%), accessibility functions such as text-to-speech and subtitles (62.5%), and the creation of mind maps, graphs and other study aids (59.8%).

Teachers also reported diversified uses. Translation was the most common specified application (75.0%), followed by creating presentations (63.5%), creating assignments (61.9%), data analysis (57.2%), improving the accessibility of lessons (56.6%) and producing mind maps, graphs and other teaching resources (50.9%).

These findings show that AI is already influencing several stages of the educational process. It is used to access and reformulate information, produce materials, support study, analyse data, design assignments and improve accessibility. Its role is therefore not confined to administrative efficiency or text generation but extends to teaching design, learning support and academic production.

At the same time, the survey measures whether a tool is used, rather than how well it is used. Frequent use cannot in itself demonstrate that AI has been integrated into clearly defined learning objectives or that its outputs are being systematically verified.

3.1.3. Functional use is more developed than competence maturity

Although use is widespread, advanced self-perceived knowledge remains uncommon. Only 7.0% of students and 6.9% of teachers described their knowledge of AI as advanced. Most respondents placed themselves at either a basic or an intermediate level.

The use of paid tools was also limited, although this indicator should not be treated as a direct measure of competence. Paid AI tools were used by 21.5% of students and 27.4% of teachers. The results therefore point mainly to an ecosystem based on accessible and often general-purpose applications.

The distinction between **functional tool use** and **educational or professional competence** is essential. The ability to obtain a translation, summary, explanation or generated text does not necessarily imply the ability to:

- select an appropriate AI system for a particular task;
- formulate and refine effective instructions;
- assess the reliability of an output;
- recognise hallucinations and bias;
- compare AI-supported and non-AI approaches;
- protect personal or sensitive data;
- disclose or cite the use of AI;
- integrate AI into discipline-specific professional practice.

The findings therefore describe a population with considerable practical exposure to AI but a much smaller group claiming advanced knowledge.

3.1.4. Demand for further training is strong, particularly among teachers

The demand for additional learning is one of the clearest findings of the survey.

Among students, 64.3% agreed or strongly agreed that they were interested in learning more about AI in general, while 64.8% expressed interest in acquiring AI competences related to their field of study.

Interest was even stronger among teachers. A total of 81.2% agreed or strongly agreed that they wanted to learn more about AI in general, and 79.9% expressed an interest in developing new AI competences within their teaching field.

The strength of this demand is particularly relevant because it coexists with relatively modest participation in formal training. The contrast between interest and training received suggests that a considerable proportion of respondents are willing to develop their competences but have not yet had access to adequate or sufficiently visible opportunities.

Teachers also expressed substantial support for institutional expansion in this area. Three quarters agreed or strongly agreed that their university should increase the number of AI courses in their field, while 63.4% agreed that universities should improve teachers' AI competences for teaching. Among students, 50.5% supported an increase in field-specific AI courses and 53.8% considered that their university should improve professors' AI skills.

3.1.5. A gap emerges between competence transfer and students' recognition of learning

One of the most important contrasts concerns the transfer of AI competences from teachers to students.

Among teachers, 64.1% stated that they transferred AI competences to students in order to improve their learning experience. An even larger proportion, 72.1%, reported transferring AI competences specific to their disciplinary field.

However, only 31.7% of students stated that they had learned AI skills from their professors.

The questions are not identical and should not be interpreted as a direct evaluation of the same teaching interaction. Teachers were asked about the competences they believed they transferred, whereas students were asked whether they perceived that they had learned AI skills from their professors. Nevertheless, the size of the difference indicates a relevant mismatch between teaching intentions and students' recognition of the learning received.

Several non-exclusive interpretations are possible. Teachers may use AI in their teaching without making the corresponding competences explicit. They may present examples or recommend tools without defining observable learning outcomes. Alternatively, students may not identify these activities as formal AI education unless they are clearly explained, practised and assessed.

The survey does not determine which explanation is correct, but it shows that the use of AI by teachers does not automatically translate into a clearly recognisable transfer of competence.

3.1.6. Ethical acceptance depends on the purpose for which AI is used

Acceptance of AI is neither unconditional nor uniform. Both students and teachers differentiate between using AI to support the production of content and using it to assess competences.

Among teachers, 79.5% considered it fair to use AI to support the creation of teaching content. Acceptance fell to 63.2% when AI was used to assess students' competences and to 56.1% when teachers were asked whether it was fair for students to use AI to complete assignments.

Among students, 65.5% considered it fair to use AI for assignments, and 64.7% accepted professors' use of AI to create materials. However, only 48.9% considered it fair for professors to use AI for assessment.

Assessment is therefore the area in which acceptance is weakest, particularly among students. The results indicate that respondents make a distinction between AI as an assistive or productive tool and AI as an instrument involved in making judgements about academic performance.

This finding also shows that ethical acceptance cannot be adequately represented by a single general question about whether respondents are "in favour of" AI. Acceptance depends on the actor using it, the purpose of the activity and the consequences of the decision supported by the technology.

3.1.7. AI is considered useful, but its educational value is not taken for granted

A majority of students reported positive effects on some aspects of learning. A total of 59.8% agreed or strongly agreed that AI helped them learn faster, 57.1% that it helped them learn better and 52.8% that it improved the quality of teaching and learning.

Teachers expressed a more cautious assessment of its direct effects on students. Among them, 47.5% agreed or strongly agreed that AI helped students learn faster, and 43.8% believed that it helped them learn better. Nevertheless, 54.4% agreed that AI improved the overall quality of teaching and learning within their degree programme.

These findings demonstrate that AI is perceived as useful, but the positive assessment is not overwhelming. In particular, faster learning should not be treated as equivalent to better or deeper learning. The data do not objectively measure academic performance and cannot establish whether AI produces improvements in learning outcomes.

The results therefore support a balanced interpretation: respondents recognise practical and educational benefits, but they do not provide evidence for an unqualified technologically optimistic conclusion.

3.1.8. Teachers perceive substantial pedagogical and ethical risks

Risk perception is especially pronounced among teachers.

A total of:

- 84.4% were concerned about the reliability of AI-generated information;
- 82.9% were concerned that AI might affect students' critical thinking;
- 79.5% were concerned that AI might increase dishonest practices;
- 40.7% were concerned that AI might replace professors in teaching activities.

The lower percentage relating to teacher replacement indicates that the principal concerns are not primarily centred on employment substitution. They focus more strongly on the quality of information, the integrity of academic work and the cognitive consequences of AI-supported learning.

Students showed a less critical assessment of the effect on their own thinking. Only 36.1% agreed or strongly agreed that AI had reduced their critical thinking. This difference may reflect the distinct positions of the two groups. Teachers assess risks across a wider range of students and academic activities, whereas students report their own perceived experience. It may also reflect different levels of awareness of the risks or different interpretations of what constitutes critical thinking.

The data do not establish whether AI actually reduces critical thinking or increases dishonesty. They show that these are highly visible concerns among teaching staff and therefore important dimensions of institutional readiness.

3.1.9. Inclusion and accessibility constitute a significant area of opportunity

Accessibility is not a marginal use within the sample. AI was used for accessibility-related purposes by 62.5% of students and by 56.6% of teachers. In addition, 63.0% of teachers reported using AI to make their lessons more accessible to students with fewer opportunities.

These results suggest that respondents already recognise applications of AI beyond productivity and content creation. Relevant uses may include automatic subtitles, text-to-speech systems, translation, simplification of materials, alternative formats and personalised forms of study support.

However, the questionnaire does not measure the quality, accessibility compliance or pedagogical appropriateness of the tools used. Reported use should therefore be understood as evidence of practical interest and existing experimentation rather than proof that the applications meet established accessibility standards.

Students were almost evenly divided in their responses to the four proposed AI-supported university services. A small numerical majority expressed interest in each service:

- 52.5% would welcome an AI tutor for administrative tasks;
- 54.6% would welcome AI-supported tutoring during internships;
- 54.9% would like access to an AI tool for initial psychological support;
- 52.8% would like to study through AI-generated lessons.

Exact binomial tests against an equal 50% distribution indicate that each proportion is statistically above the midpoint ($p < 0.01$). However, the differences from 50% range from only 2.5 to 4.9 percentage points. Given the large, voluntary and non-probability-based sample, these results should not be interpreted as evidence of strong or generalised demand. They indicate a slight majority in favour within the surveyed sample, while substantial proportions of students did not support each proposed service.

The results therefore justify further consultation or carefully evaluated pilot initiatives, rather than broad implementation based solely on the questionnaire. In particular, applications involving psychological support would require a substantially different level of ethical control, professional supervision and risk management from lower-risk administrative services.

In particular, applications involving psychological support would require a substantially different level of ethical control, professional supervision and risk management from low-risk administrative services.

3.1.10. Aggregate results conceal substantial institutional variation

The detailed tables prepared separately for students and teachers show that the general findings are not distributed uniformly across institutions.

Among students in the largest named institutional samples, the proportion using AI often or always was 40.3% at Asfendiyarov Kazakh National Medical University and 48.0% at Tashkent State Pedagogical University. At Astana IT University, the proportion was higher, at 57.4%, although the sample was smaller (N = 148).

Variation was even more pronounced among teachers. AI was used often or always by 36.0% of teachers from Asfendiyarov Kazakh National Medical University, compared with 85.5% at Tashkent State Pedagogical University. The corresponding figure at Yangi Asr University was 90.7%, although this result was based on only 43 teachers.

Similar institutional differences were found in relation to training, guidelines, knowledge and competence transfer. These variations indicate that the aggregate percentages should not be interpreted as describing a single, homogeneous AI environment.

At the same time, the institutional differences cannot automatically be attributed to the universities themselves. University, country, academic field, questionnaire language and sample composition are partially interrelated. For example, an institution specialising in medicine may differ from a pedagogical or information technology university in both the professional applications of AI and the profile of its respondents.

The disaggregated results are therefore valuable for identifying institutional needs, but they should not be interpreted as institutional rankings or as evidence of causal effects.

3.1.11. Overall interpretation

Taken together, the findings indicate that EduCATIA is operating in an environment in which the initial adoption of AI has already occurred. Students and teachers are using AI across a wide range of academic activities, and both groups demonstrate clear interest in further developing their competences.

The principal weakness lies not in a general lack of access or willingness, but in the limited transformation of practical use into:

- advanced and critical competence;
- structured teacher capacity;
- explicit and recognisable learning outcomes;
- discipline-specific curricular provision;
- clear institutional guidance;
- transparent assessment practices;
- reliable and ethically supervised applications.

The strongest overall conclusion is therefore that the surveyed institutions are experiencing **broad AI adoption but uneven educational maturity**. AI use is already widespread, but its pedagogical, ethical and institutional foundations remain only partially developed.

This conclusion provides the central interpretative framework for the more detailed presentation of student and teacher results in the following sections.

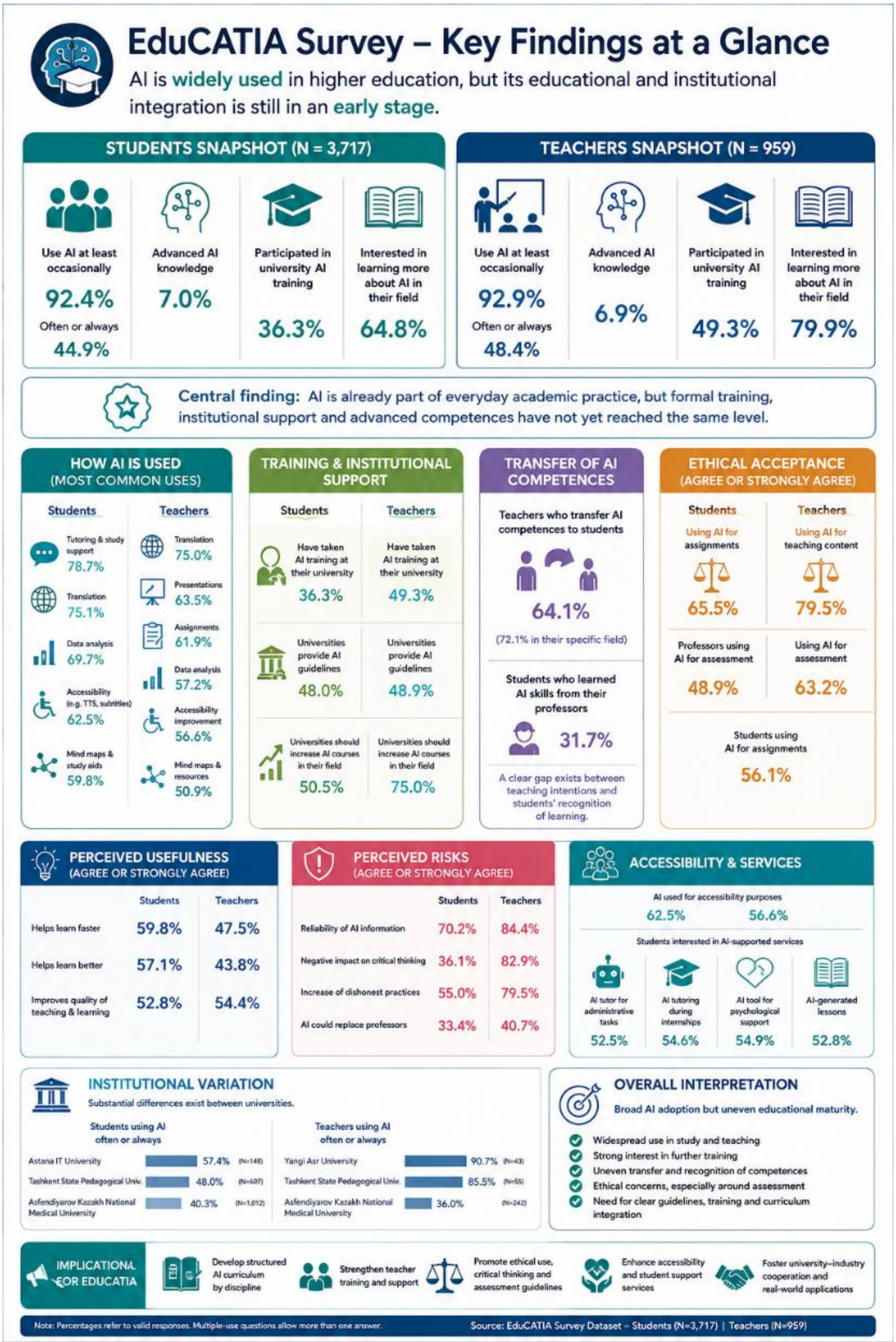

Figure 1. EduCATIA Survey - Key Findings at a Glance

Source: EduCATIA final survey dataset, student questionnaire, valid N = 3,717; teacher questionnaire, valid N = 960. Separate student and teacher tables prepared by Simona Perone were used to verify the general calculations and examine institutional differences.

Analytical note: Percentages reported for four-point agreement scales combine “agree” and “strongly agree”. Percentages relating to different AI uses are based on separate binary questions and should not be added together.

3.2. Results for students

The final student sample comprised **3,717 respondents**. All substantive questions included in the analysis contained a recorded response in the cleaned dataset. The findings therefore use a valid N of 3,717 unless otherwise stated.

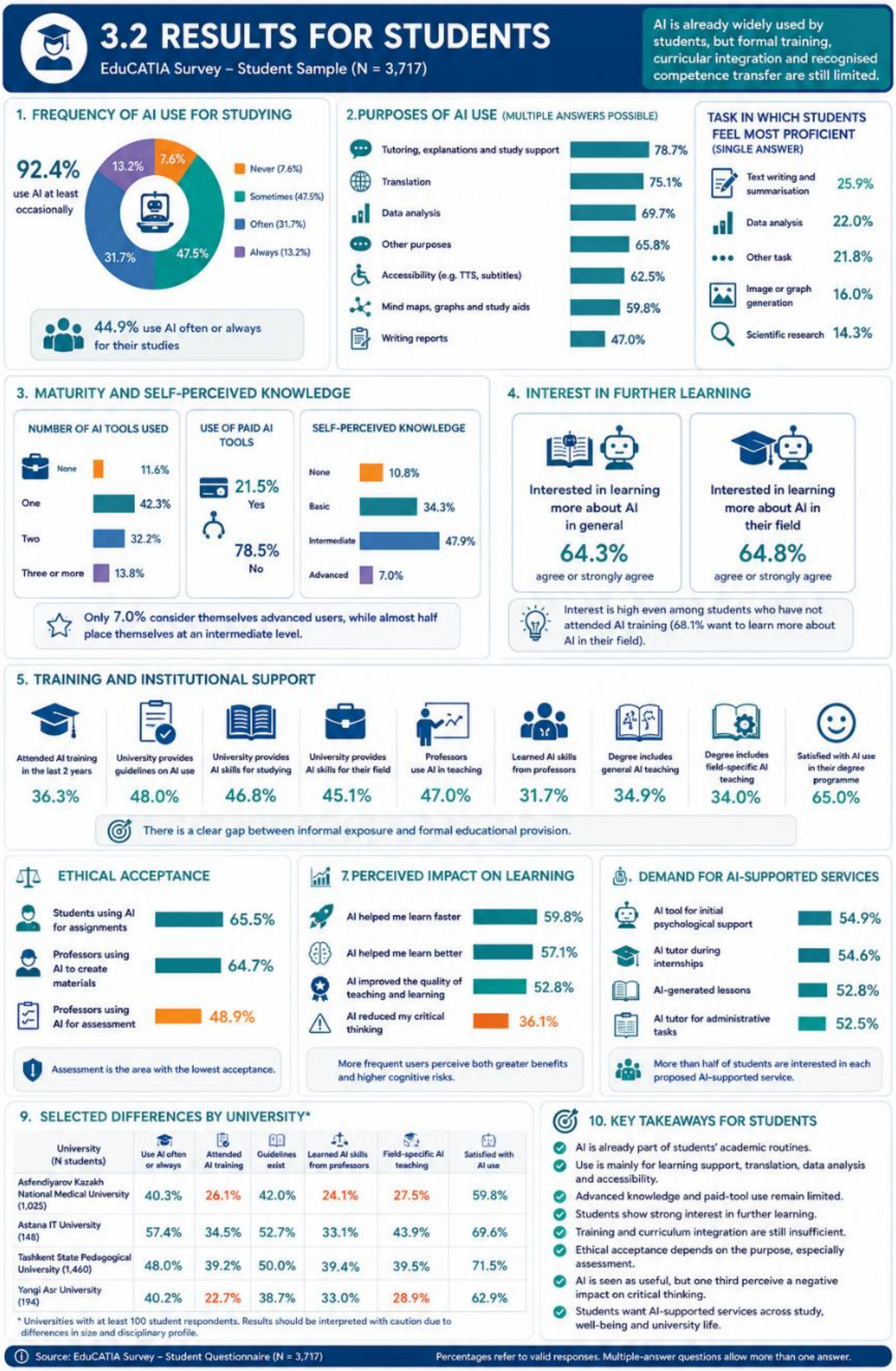

Figure 2. Results for Students

The results show that AI is already widely present in students' academic practices. However, the breadth of use is not matched by an equivalent level of advanced knowledge, formal training, curriculum integration or recognised competence transfer from teachers. Students generally perceive AI as useful and show considerable interest in further learning, but their acceptance varies according to the purpose for which AI is used, particularly when assessment is involved.

3.2.1. Frequency and purposes of AI use

Only 281 students, representing 7.6% of the sample, reported that they never used AI for studying. Almost half used it sometimes, while 44.9% used it often or always.

Table 3.2. Frequency of AI use for studying

Frequency	n	%
Never	281	7.6
Sometimes	1,766	47.5
Often	1,179	31.7
Always	491	13.2
Total	**3,717**	**100.0**

The results indicate that occasional use has become normalised, but intensive or systematic use is not yet universal. The largest group consisted of students who used AI sometimes, suggesting that AI is broadly accessible but incorporated into study routines with different levels of regularity.

Students used AI for a wide range of purposes rather than for one dominant activity alone.

Table 3.3. Purposes for which students use AI

Purpose	Yes, n	Yes, %
Tutoring, explanations and study support	2,927	78.7
Translation	2,791	75.1
Data analysis	2,590	69.7
Other purposes	2,444	65.8
Accessibility, including text-to-speech and subtitles	2,324	62.5
Mind maps, graphs and study aids	2,221	59.8
Writing reports	1,748	47.0

Note: These were separate binary items. Respondents could report more than one use, and the percentages should therefore not be added together.

Tutoring, explanations and study support constituted the most common use, reported by almost four out of five students. This finding suggests that AI is functioning primarily as an individual learning assistant. Translation was almost equally widespread, which is particularly relevant in a multilingual project context. Data analysis was also reported by more than two thirds of respondents.

The use of AI for accessibility was substantial. Almost two thirds of students reported using applications such as text-to-speech systems or subtitles. This indicates that accessibility-related functions are already part of actual student practice and are not merely a hypothetical future application.

Report writing was the least frequently selected of the specified uses, although it was still reported by almost half of the sample. The high percentage selecting “other purposes” indicates that the closed categories did not capture the full diversity of student practices. Since the questionnaire did not ask respondents to specify these additional purposes, this category cannot be interpreted more precisely.

When asked to identify the AI task in which they felt most proficient, students most frequently selected text writing and summarisation.

Table 3.4. AI task in which students feel most proficient

Task	n	%
Text writing and summarisation	963	25.9
Data analysis	818	22.0
Other task	810	21.8
Image or graph generation	596	16.0
Scientific research	530	14.3
Total	**3,717**	**100.0**

The distribution is relatively dispersed. No single task was selected by more than approximately one quarter of the sample. In particular, only 14.3% identified scientific research as the area in which they felt most proficient, despite the frequent use of AI for data analysis and study support.

This item was analysed as a single-response question because the final dataset contains one coded category for each respondent.

3.2.2. Number of tools, paid access and self-perceived knowledge

Most students used a limited number of AI tools. A total of 11.6% reported using none, 42.3% used one tool, 32.2% used two and 13.8% used three or more.

Table 3.5. Indicators of student AI maturity

Indicator	Category	n	%
Number of AI tools used	None	433	11.6
	One	1,573	42.3

	Two	1,198	32.2
	Three or more	513	13.8
Use of paid AI tools	Yes	799	21.5
	No	2,918	78.5
Self-perceived knowledge	None	401	10.8
	Basic	1,274	34.3
	Intermediate	1,782	47.9
	Advanced	260	7.0

Although 92.4% used AI at least occasionally, only 7.0% considered their knowledge advanced. Almost half described their knowledge as intermediate, while 45.1% placed themselves at either the basic level or reported no knowledge.

The use of paid tools was also limited to approximately one student in five. Paid access should not be interpreted as a measure of competence, since free tools may be sufficient for many academic tasks and ability to pay may differ between respondents. Nevertheless, the combination of limited tool diversity, low paid-tool use and a small advanced group suggests that most students operate within a relatively accessible, general-purpose AI environment.

Frequency of use and self-perceived knowledge were related, but they were not equivalent. Among students who always used AI, 14.1% described their knowledge as advanced. This was higher than among students who used it often, sometimes or never, but it still meant that most intensive users did not consider themselves advanced.

3.2.3. Interest in further learning

Student interest in additional AI learning was substantial.

A total of 64.3% agreed or strongly agreed that they wanted to learn more about AI in general. A similar proportion, 64.8%, wanted to acquire further knowledge relating specifically to their field of study.

Table 3.6. Student interest in further AI learning

Statement	**Agree or strongly agree, n**	**Agree or strongly agree, %**
Interested in learning more about AI in general	2,391	64.3
Interested in learning more about AI in their field	2,410	64.8

The similarity between the two indicators suggests that students seek both general AI literacy and discipline-specific competence. Their interest is therefore not limited to learning how to operate individual tools. It also concerns the use and meaning of AI within their future academic and professional fields.

Interest was not restricted to students who had already received training. Among those who had not attended a university AI-training activity during the previous two years, 68.1% expressed an interest in learning more about AI in their field. The corresponding figure among students who had already received training was 59.1%.

This descriptive difference may indicate that students without previous training perceive a greater unmet need. It should not be interpreted as evidence that training reduces interest, since the groups may differ in their institutions, fields, prior experience and expectations.

3.2.4. Training and institutional support

Institutional support was less widespread than individual use.

Only 36.3% of students had participated in an AI-training activity at their university during the previous two years. Fewer than half reported that their university provided AI guidelines, general study-related AI competences or competences applied to their field.

Table 3.7. Student perceptions of institutional support and curriculum integration

Indicator	Yes, n	Yes, %
Attended university AI training during the previous two years	1,350	36.3
University provides guidelines on AI use	1,784	48.0
University provides AI skills for studying	1,740	46.8
University provides AI skills for the student's field	1,676	45.1
Professors use AI in teaching	1,747	47.0
Student learned AI skills from professors	1,179	31.7
Degree includes general AI teaching	1,296	34.9
Degree includes field-specific AI teaching	1,265	34.0
Satisfied with AI use in the degree programme	2,415	65.0

The findings show a consistent difference between informal exposure and formal educational provision. AI was used by more than nine out of ten students, but only around one third reported receiving training or studying AI through their degree programme.

The questionnaire also reveals a distinction between the visibility of teachers' AI use and the transfer of student competences. While 47.0% stated that their professors used AI in teaching, only 31.7% reported having learned AI skills from their professors.

Among the 1,747 students who reported that their professors used AI, 954, or 54.6%, also stated that they had learned AI skills from them. The remaining 45.4% did not perceive that teachers' use of AI had resulted in the acquisition of a recognisable competence.

This does not demonstrate that teaching was ineffective. Professors may use AI for preparing materials or supporting classroom processes without making AI competence an explicit learning outcome. However, the finding confirms that exposure to teacher use and perceived competence acquisition are distinct phenomena.

The results concerning institutional guidelines require particular caution. Among students who stated that guidelines existed, 73.3% described them as clear or very clear, while 23.8% described them as unclear or very unclear. A further 2.9% selected “no guidelines” in the subsequent clarity question despite previously indicating that guidelines existed.

More generally, some students who answered that their university did not provide guidelines nevertheless rated their clarity. This internal inconsistency suggests that respondents may have interpreted “guidelines” differently or may have referred to informal instructions, course-level rules or general university policies. The existence and clarity items should therefore be analysed separately rather than combined automatically into a single indicator.

3.2.5. Curriculum integration and satisfaction

Only 34.9% of students reported that their degree included general AI teaching, and 34.0% reported field-specific AI teaching. These similar results indicate that formal curriculum provision remains limited for both general and disciplinary AI competence.

Nevertheless, 65.0% stated that they were satisfied with the use of AI in their degree programme. This apparently more positive result should not be interpreted as evidence that AI provision is comprehensive. Satisfaction may reflect limited expectations, appreciation of individual initiatives or positive experiences among students who encounter AI in particular courses.

Satisfaction was much higher among students who reported explicit curriculum integration:

- 87.1% of students whose degree included field-specific AI teaching were satisfied, compared with 53.5% of those whose degree did not;
- 86.8% of students whose degree included general AI teaching were satisfied, compared with 53.3% of those whose degree did not;
- 81.1% of students whose professors used AI were satisfied, compared with 50.7% of those who did not report teacher use.

Chi-square tests of independence confirmed that satisfaction was significantly associated with each of the three indicators. Students reporting field-specific AI teaching were more likely to be satisfied than those who did not report such provision, $\chi^2(1, N = 3{,}717) = 413.1$, $p < 0.001$, Cramér’s $V = 0.333$. A similar association was observed for general AI teaching, $\chi^2(1, N = 3{,}717) = 416.8$, $p < 0.001$, Cramér’s $V = 0.335$, and for professors’ use of AI in teaching, $\chi^2(1, N = 3{,}717) = 374.6$, $p < 0.001$, Cramér’s $V = 0.317$. All three results remain statistically significant after adjustment for the three comparisons.

These results indicate clear associations within the analytical sample, with differences in satisfaction of approximately 30 to 34 percentage points. However, they do not establish that curriculum integration or professors’ use of AI caused higher satisfaction. Satisfaction and reported provision may both be influenced by university, academic field, previous experience, attitudes towards AI or other unmeasured factors. Moreover, because the survey used a voluntary, non-probability sample, the tests should not be interpreted as supporting statistical generalisation to the wider student populations of the participating countries.

3.2.6. Ethical acceptance of AI use

Student acceptance varied according to the activity and the person using AI.

Table 3.8. Student acceptance of selected AI uses

Use of AI considered fair	**Yes, n**	**Yes, %**
Students using AI for assignments	2,433	65.5
Professors using AI to create materials	2,406	64.7
Professors using AI for assessment	1,817	48.9

Approximately two thirds considered it fair for students to use AI for assignments and for professors to use it when creating educational materials. Acceptance fell below half when AI was used by professors for assessment.

The similarity between acceptance of student assignment use and teacher material creation suggests a relatively broad acceptance of AI as a tool for supporting production. By contrast, the lower acceptance of AI-assisted assessment shows greater caution when AI contributes to decisions about academic performance.

The questionnaire did not specify whether AI would operate autonomously, provide recommendations to a teacher or perform only administrative functions within assessment. The result should therefore be interpreted as a general indication that assessment is more ethically sensitive, rather than as rejection of every possible assessment-related application.

3.2.7. Perceived effects on learning and critical thinking

A majority of students perceived educational benefits from AI, although agreement was not universal.

Table 3.9. Perceived effects of AI on students' learning

Statement	**Agree or strongly agree, n**	**Agree or strongly agree, %**
AI helped me learn faster	2,224	59.8
AI helped me learn better	2,124	57.1
AI improved the quality of teaching and learning	1,963	52.8
AI reduced my critical thinking	1,341	36.1

Students were slightly more likely to perceive an improvement in speed than an improvement in the quality of their learning. This distinction is important: greater efficiency does not necessarily mean deeper comprehension, better retention or greater independence.

Just over half believed that AI had improved the overall quality of teaching and learning. The result is positive but not sufficiently strong to suggest a uniform student experience.

Most students did not agree that AI had reduced their critical thinking. In total, 63.9% disagreed or strongly disagreed with this statement. Nevertheless, more than one third perceived at least some negative effect on their critical thinking, which constitutes a relevant minority.

Perceptions varied according to frequency of use. Among students who used AI often or always:

- 69.4% stated that it helped them learn faster, compared with 52.0% among those using it never or sometimes;
- 67.7% stated that it helped them learn better, compared with 48.6%;
- 40.4% stated that it reduced their critical thinking, compared with 32.6%.

More frequent users therefore reported both greater benefits and somewhat greater awareness of possible cognitive costs. This pattern supports a balanced interpretation of AI experience: intensive use is associated with stronger perceived utility, but it does not eliminate concern about dependency or reduced independent reflection.

No causal conclusion can be drawn from these associations. Students who perceive AI as useful may choose to use it more frequently, while frequent experience may also influence perceptions of both benefit and risk.

3.2.8. Demand for AI-supported university services

More than half of the students expressed interest in each of the four proposed AI-supported services.

Table 3.10. Student demand for AI-supported services

Proposed service	Yes, n	Yes, %
AI tool for initial psychological support	2,040	54.9
AI tutor during internships	2,030	54.6
AI-generated lessons	1,963	52.8
AI tutor for university administrative tasks	1,950	52.5

The results show moderate rather than overwhelming demand. Support ranged from 52.5% to 54.9%, meaning that substantial minorities did not express interest in the proposed services.

The greatest demand concerned initial psychological support, although the difference from the other services was small. The response indicates openness to such a service but does not demonstrate willingness to replace qualified psychological professionals. The wording referred specifically to initial support, and the questionnaire did not examine expectations regarding confidentiality, human supervision, emergency management or the limitations of automated systems.

Interest in AI tutoring during internships was similarly widespread. This finding is particularly relevant to the project's interest in university-to-work transitions, although the responses do not specify which forms of tutoring students would consider most useful.

3.2.9. Selected differences between countries and institutions

The detailed tables show that the overall results conceal institutional variation. These differences must be interpreted cautiously because universities differ in size, disciplinary profile, country, questionnaire language and composition of their student populations.

At country level, the two largest samples displayed similar rates of general adoption:

- 44.6% of students reporting Kazakhstan and 45.8% of those reporting Uzbekistan used AI often or always;
- 36.2% and 36.4%, respectively, had attended university AI training;
- 49.1% and 47.4%, respectively, reported the existence of university guidelines.

These similarities suggest that the overall difference between the two principal national samples is limited for basic adoption, training participation and reported guidelines.

Other indicators differed more clearly. Field-specific interest was reported by 78.0% of students in the Kazakhstan sample and 54.1% in the Uzbekistan sample. Conversely, 38.4% of students in the Uzbekistan sample stated that they had learned AI skills from professors, compared with 22.1% in the Kazakhstan sample. Field-specific AI teaching was reported by 37.9% and 28.4%, respectively.

These contrasts should not be interpreted as independent national effects. The Kazakhstan sample is strongly influenced by medical institutions, while the Uzbekistan sample contains a large proportion of education students. Differences may therefore reflect disciplinary and institutional composition rather than national policy or culture.

The following table presents selected indicators for named universities with at least 100 student respondents.

Table 3.11. Selected student indicators by university

University	**Valid N**	**Use AI often or always, %**	**Attended AI training, %**	**Guidelines exist, %**	**Learned AI skills from professors, %**	**Degree includes field-specific AI, %**	**Satisfied with AI use, %**
Asfendiyarov Kazakh National Medical University	1,025	40.3	26.1	42.0	24.1	27.5	59.8
Astana IT University	148	57.4	34.5	52.7	33.1	43.9	69.6
Tashkent State Pedagogical University	1,460	48.0	39.2	50.0	39.4	39.5	71.5

Yangi Asr University	194	40.2	22.7	38.7	33.0	28.9	62.9

Note: Sapienza University of Rome and the University of Freiburg are not included in this comparative table because their student samples were below 100. Results for small institutional samples remain available in the detailed tables but should not be used for institutional ranking.

Astana IT University recorded the highest proportion of frequent users among the institutions shown, while Tashkent State Pedagogical University reported comparatively stronger training participation, competence transfer and field-specific integration than the two large medical and multidisciplinary institutions.

However, these findings should not be interpreted as evidence that one institution performs better overall. The universities have different disciplinary missions, student profiles and sample sizes, and no adjustment or weighting was applied for these differences.

3.2.10. Differences by academic field and gender

The two largest academic groups were medicine, with 1,469 students, and education, with 1,291.

Students in education reported somewhat more frequent AI use than students in medicine: 48.6% used it often or always, compared with 43.2%. Education students were also more likely to report:

- university AI training: 40.9%, compared with 36.0% in medicine;
- learning AI skills from professors: 41.3%, compared with 21.8%;
- field-specific AI teaching in their degree: 41.2%, compared with 27.4%.

By contrast, interest in learning more about AI within their field was considerably higher among medicine students: 78.4%, compared with 55.1% among education students.

These findings point to different profiles of need. Education students reported greater exposure to AI through teachers and curricula, whereas medicine students showed particularly strong demand for further discipline-specific learning despite reporting less formal integration.

Students in computer science reported a high rate of frequent use, at 60.2%, but the group contained only 93 respondents. Psychology and biomedical sciences also had small samples, with 68 and 51 respondents respectively. Results for these groups should be regarded as exploratory and should always be presented together with their valid N.

Differences between male and female students were generally modest:

- 43.4% of male and 45.4% of female students used AI often or always;
- 37.7% and 36.0%, respectively, had attended university training;
- 8.2% of male and 6.6% of female students described their knowledge as advanced;
- 63.5% and 65.8%, respectively, wanted to learn more about AI in their field.

The survey therefore does not show a large gender gap in reported access, use or interest within the sample. Nevertheless, this conclusion concerns self-reported participation and does not measure the quality of access, confidence in specific tasks, barriers to advanced training or objective competence.

3.2.11. Summary of the student results

The student results reveal an academic environment in which AI use is already widespread and functionally diverse. Students employ it primarily for tutoring and explanations, translation, data analysis, accessibility and the production of study resources.

At the same time, the results show a lower level of educational institutionalisation. Only around one third had received recent university training or reported general or field-specific AI teaching within their degree. Fewer than one third stated that they had learned AI competences from their professors, despite almost half reporting that professors used AI in teaching.

Students generally perceived AI as useful and expressed a clear interest in further learning. However, advanced self-perceived knowledge remained uncommon, and ethical acceptance was selective. AI was more readily accepted for supporting assignments and creating materials than for assessment.

The findings also show that students do not perceive AI in exclusively positive terms. A majority reported benefits for learning, but more than one third believed that it had reduced their critical thinking. More frequent users reported both stronger benefits and greater perceived cognitive risk.

Overall, student adoption is more advanced than formal curriculum integration. The evidence points to a transition from individual, general-purpose and often informal use towards a demand for more explicit, discipline-specific and institutionally recognisable AI education.

Source: EduCATIA survey final dataset, student questionnaire, questions 7–43, valid N = 3,717. The separate student tables were used to verify totals and examine differences by country, university, academic field and gender.

Methodological note: Percentages for Likert-type questions combine “mostly agree” and “strongly agree”. Percentages for separate AI-use items are not mutually exclusive. All subgroup comparisons are descriptive and unweighted.

3.3. Results for teachers

Following the incorporation of the additional verified questionnaire from the University of Freiburg, the teacher sample analysed in this section comprises **960 respondents**. All substantive questions from Q7 to Q40 contain a valid response.

The findings show that AI is already widely used in teaching and across a diverse range of academic tasks. Teachers also demonstrate a strong interest in further training and generally recognise the potential educational value of AI. However, advanced self-perceived knowledge remains uncommon, formal training and institutional guidelines reach only around half of the sample, and concerns about reliability, academic integrity and critical thinking are widespread.

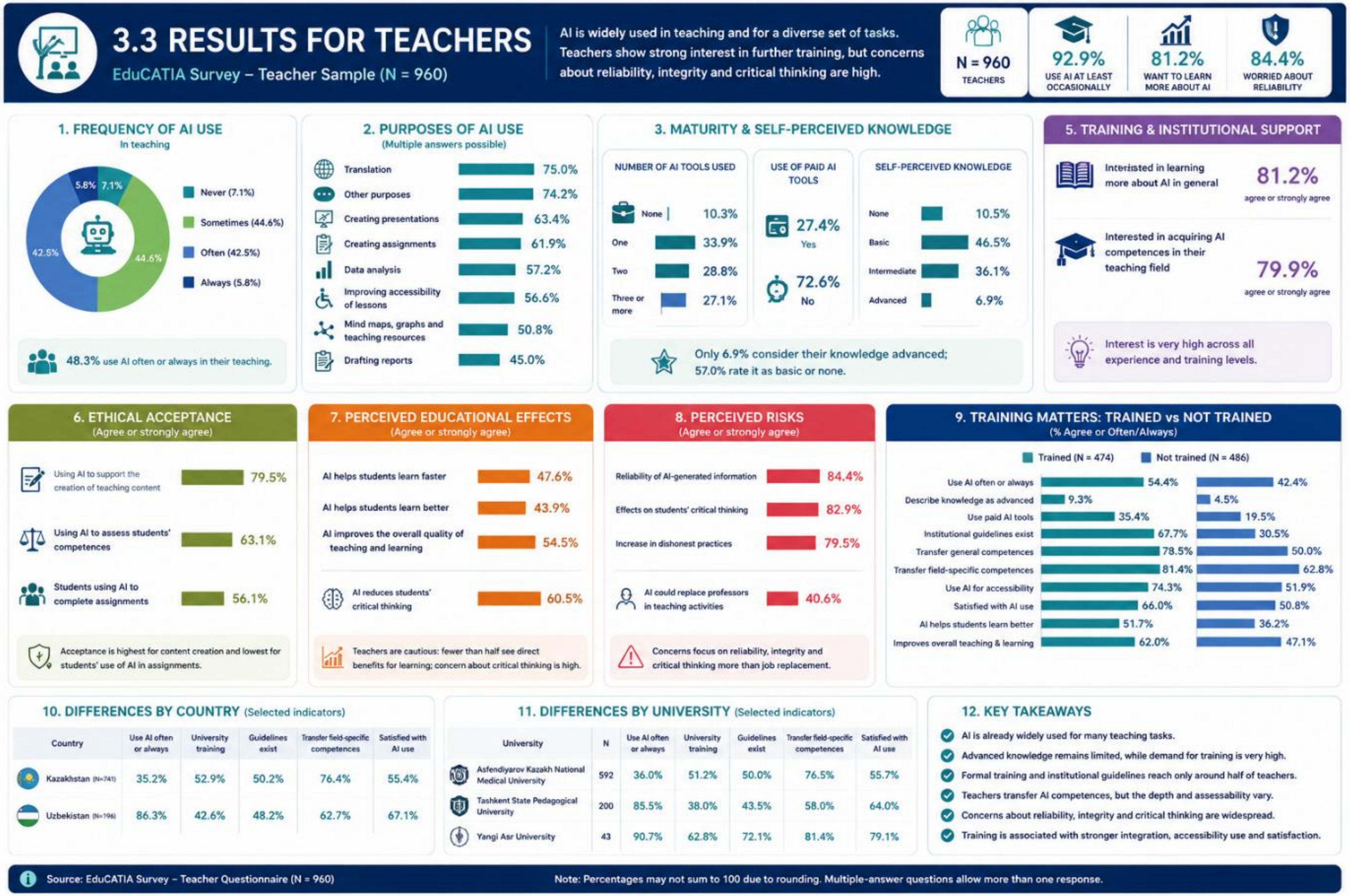

Figure 3. Results for Teachers

3.3.1. Frequency and purposes of AI use in teaching

Only 68 teachers, representing 7.1% of the sample, reported never using AI in their teaching. A further 44.6% used it sometimes, while 48.3% used it often or always.

Table 3.12. Frequency of AI use in teaching

Frequency	**n**	**%**
Never	68	7.1
Sometimes	428	44.6
Often	408	42.5
Always	56	5.8
Total	**960**	**100.0**

Overall, 92.9% of teachers used AI at least occasionally. The relatively small proportion selecting "always" suggests that intensive use remains less common than periodic or task-specific use. Nevertheless, AI is already part of the professional practice of a clear majority of the teaching staff surveyed.

Teachers reported using AI for a broad range of activities.

Table 3.13. Purposes for which teachers use AI

Purpose	**Yes, n**	**Yes, %**
Translation	720	75.0
Other purposes	712	74.2
Creating presentations	609	63.4
Creating assignments	594	61.9
Data analysis	549	57.2
Improving lesson accessibility	543	56.6
Mind maps, graphs and other teaching resources	488	50.8
Drafting reports	432	45.0

Note: These were separate binary questions. Respondents could report more than one use, and the percentages should therefore not be added together.

Translation was the most common specified use, reported by three quarters of teachers. This finding is particularly relevant in the multilingual context of EduCATIA. AI was also widely used to create presentations and assignments, demonstrating that it is already influencing the preparation and design of teaching activities.

More than half of the teachers used AI for data analysis and to improve the accessibility of their lessons. Approximately half used it to produce mind maps, graphs and other teaching resources.

The high proportion selecting "other purposes" indicates that the questionnaire categories did not fully capture the diversity of teachers' practices. Since respondents were not asked to describe these uses, the category cannot be interpreted in greater detail.

The findings demonstrate functional diversity, but they do not establish the pedagogical quality of these practices. The use of AI to create an assignment, presentation or accessible resource does not in itself indicate whether the output was verified, aligned with learning outcomes or adapted appropriately to the needs of students.

3.3.2. Number of tools, paid access and self-perceived knowledge

Teachers generally reported using more than one AI tool, although advanced self-perceived knowledge remained limited.

Table 3.14. Indicators of teacher AI maturity

Indicator	Category	n	%
Number of AI tools used	None	99	10.3
	One	325	33.9
	Two	276	28.8
	Three or more	260	27.1
Use of paid AI tools	Yes	263	27.4
	No	697	72.6
Self-perceived knowledge	None	101	10.5
	Basic	446	46.5
	Intermediate	347	36.1
	Advanced	66	6.9

More than half of the teachers used at least two AI tools, and 27.1% reported using three or more. However, only 6.9% considered their knowledge advanced. A majority, 57.0%, placed themselves at either the basic level or reported no AI knowledge.

This apparent contrast reinforces the distinction between using several tools and possessing advanced educational or professional competence. Teachers may use multiple applications for translation, presentations or content production without necessarily having developed deeper knowledge of how AI systems operate, how their outputs should be evaluated or how they should be integrated into curriculum and assessment design.

The use of paid tools was reported by 27.4% of respondents. Paid access does not constitute a direct measure of competence, since it may depend on institutional provision, personal resources and the specific applications required. Nevertheless, the result indicates that most teachers rely primarily on free or institutionally accessible services.

Frequency of use was associated with self-perceived knowledge. Among teachers who always used AI, 23.2% described their knowledge as advanced. The corresponding proportion was 9.6% among those using it often and below 3% among teachers using it sometimes or never.

This relationship is descriptive and does not establish whether frequent use develops knowledge or whether more knowledgeable teachers are more likely to use AI regularly.

3.3.3. Interest in further learning

Teachers expressed a particularly strong demand for further learning.

A total of 81.2% agreed or strongly agreed that they were interested in learning more about AI in general. A similarly high proportion, 79.9%, wanted to acquire new AI competences related to their own teaching field.

Table 3.15. Teacher interest in further AI learning

Statement	Agree or strongly agree, n	Agree or strongly agree, %
Interested in learning more about AI in general	780	81.2
Interested in acquiring AI competences in their teaching field	767	79.9

The similarity between the two results shows that teachers seek both general AI literacy and discipline-specific application. Their demand is not limited to gaining familiarity with new tools; it includes the integration of AI into their particular academic and professional contexts.

Interest remained high even among teachers who had already attended training. Among trained teachers, 84.0% wanted to develop further field-specific competences. Among teachers without previous university training, the corresponding proportion was 75.9%.

This indicates that participation in one training activity does not exhaust the need for continued professional development. Given the rapid evolution of AI technologies, teacher training should be understood as a continuing and progressively specialised process rather than as a single introductory intervention.

3.3.4. Training and institutional support

Institutional provision was substantially less widespread than individual use and interest.

Table 3.16. Teacher training and institutional support

Indicator	Yes, n	Yes, %
Participated in university-organised AI training	474	49.4
University provides guidelines on AI use	469	48.9
Transfers general AI competences to students	615	64.1

Transfers field-specific AI competences to students	691	72.0
Uses AI to improve accessibility for students with fewer opportunities	604	62.9
Satisfied with own use of AI in teaching	560	58.3

Approximately half of the teachers had participated in an AI-training activity organised by their university during the previous two years. This is considerably lower than the proportion interested in further learning, suggesting that institutional training provision has not yet met the level of expressed demand.

Similarly, 48.9% reported that their university provided guidelines on the use of AI by professors. The result indicates that institutional governance remains uneven: approximately half of the respondents were working without recognised university-level guidance or were unaware of its existence.

The item concerning institutional guidelines measures respondents' reported awareness or recognition of guidance rather than the independently verified existence of a formal university-wide policy. The questionnaire did not define the documentary or administrative criteria that a measure had to meet in order to be considered a "guideline", nor were respondents' answers compared with an institutional register of approved policies. Participants may therefore have referred to formal university policies, faculty- or department-level instructions, course rules, recommendations received during training activities, or general academic-integrity guidance applied to AI. The results should consequently be interpreted as an indicator of the visibility and perceived availability of guidance, not as an institutional audit.

The clarity question produced a more complex pattern:

- 57.3% of all teachers described the guidelines as clear or very clear;
- 19.0% described them as unclear or very unclear;
- 23.8% selected the option indicating that no guidelines existed.

These percentages do not correspond perfectly with the preceding binary question on whether guidelines were available. Among the 469 teachers who stated that guidelines existed, 73.6% described them as clear or very clear, but 11.3% subsequently selected "no guidelines". Conversely, some respondents who initially stated that guidelines did not exist nevertheless evaluated them as clear.

This inconsistency may reflect different understandings of what constitutes an institutional guideline. Respondents may have been referring variously to university-wide policies, instructions issued by an individual faculty, informal recommendations or rules established within a particular course.

The two variables should therefore remain analytically separate. They should not be combined automatically into a single institutional-readiness score without first defining how contradictory responses will be treated.

3.3.5. Transfer of competences and accessibility

Almost two thirds of teachers stated that they transferred general AI competences to students to improve their learning experience. An even larger proportion, 72.0%, reported transferring AI competences specific to their field.

The higher value for field-specific transfer suggests that teachers may find it easier to introduce AI through concrete disciplinary applications than through a general competence framework. However, the questionnaire does not identify which competences were transferred or whether they were formally incorporated into learning outcomes and assessment criteria.

Competence transfer may include activities of very different depth, such as:

- demonstrating a particular tool;
- recommending an AI service;
- teaching students how to formulate prompts;
- requiring verification of AI-generated information;
- analysing bias and limitations;
- applying AI to discipline-specific cases;
- assessing students' ability to use AI responsibly.

The survey does not distinguish between these levels. A positive response should therefore be interpreted as a declaration of teaching practice rather than as evidence that a complete competence-based curriculum has been implemented.

A total of 62.9% reported using AI to make their lessons more accessible to students with fewer opportunities. This finding is particularly relevant to the inclusion objectives of EduCATIA. It indicates that accessibility is already perceived as a practical use of AI by a substantial proportion of teachers.

Nevertheless, the questionnaire does not establish whether the tools meet formal accessibility requirements or whether students with disabilities and other access needs were involved in their selection and evaluation. The result identifies an important area of existing practice and potential development rather than demonstrating the quality of the accessibility measures adopted.

3.3.6. Ethical acceptance and satisfaction

Teachers' ethical acceptance varied according to the purpose for which AI was used.

Table 3.17. Teacher acceptance of selected AI uses

Use considered fair	Yes, n	Yes, %
Using AI to support the creation of teaching content	763	79.5
Using AI to assess students' competences	606	63.1
Students using AI to complete assignments	539	56.1

Acceptance was highest when teachers used AI to support content creation. Almost four out of five considered this fair.

Acceptance declined when AI was involved in assessment and was lowest when students used it to complete assignments. The results suggest that teachers distinguish between AI as a tool supporting professional preparation and AI as a technology that may affect evidence of student performance.

Nevertheless, a majority accepted all three uses. The survey therefore does not indicate general opposition to AI in assessment or student work. Rather, it reveals different levels of caution depending on the actor, purpose and educational consequences.

The questions did not specify the degree of human supervision, the requirement to disclose AI use or whether AI would support rather than replace professional judgement. These factors are likely to influence acceptance and should be addressed in subsequent qualitative analysis and institutional guidelines.

A total of 58.3% of teachers were satisfied with their own use of AI in teaching. This represents a majority but also indicates that a substantial proportion were either dissatisfied or had not yet developed practices they considered satisfactory.

Satisfaction should not be interpreted as an objective measure of educational effectiveness. It reflects respondents' evaluation of their own experience and may be influenced by access to tools, training, confidence and institutional support.

3.3.7. Perceived educational effects

Teachers expressed a more cautious view of the direct benefits of AI for student learning.

Table 3.18. Teachers' perceptions of the educational effects of AI

Statement	Agree or strongly agree, n	Agree or strongly agree, %
AI helps students learn faster	457	47.6
AI helps students learn better	421	43.9
AI reduces students' critical thinking	581	60.5
AI improves the overall quality of teaching and learning	523	54.5
University should increase AI courses in the teacher's field	720	75.0
University should improve professors' AI competences	609	63.4

Fewer than half of the teachers agreed that AI helped students learn faster or better. The assessment of learning quality was therefore more cautious than the level of practical adoption might suggest.

A somewhat larger proportion, 54.5%, believed that AI improved the overall quality of teaching and learning. This may indicate that teachers perceive benefits for the wider educational process—including the preparation of materials, accessibility or teaching organisation—even when they remain uncertain about direct improvements in student learning.

At the same time, 60.5% believed that AI reduced students' critical thinking. This indicates a substantial tension between perceived usefulness and concern about the cognitive consequences of AI-supported learning.

Support for institutional action was stronger than confidence in current educational outcomes. Three quarters agreed that their university should increase AI courses in their field, while 63.4% believed that universities should improve professors' AI competences for teaching.

The results suggest that teachers do not view training as necessary only because they reject or fear AI. On the contrary, many use it and perceive potential benefits while also recognising that its effective educational integration requires stronger professional competence.

3.3.8. Perception of risks

The strongest teacher responses concerned the risks associated with AI.

Table 3.19. Teachers' concerns about AI

Concern	Yes, n	Yes, %
Reliability of AI-generated information	810	84.4
Effects on students' critical thinking	796	82.9
Increase in dishonest practices	763	79.5
Replacement of professors in teaching activities	390	40.6

Reliability was the most widespread concern. More than four out of five teachers were concerned about the accuracy and trustworthiness of AI-generated information. This finding is particularly important in disciplines in which incorrect information may have significant educational, clinical or professional consequences.

Concern about students' critical thinking was almost equally widespread, while 79.5% feared an increase in dishonest practices.

By contrast, concern that AI might replace professors was reported by 40.6%. Although this constitutes a substantial minority, it is considerably lower than concern about reliability, integrity and critical thinking.

The pattern indicates that teachers' principal concerns are pedagogical and ethical rather than centred exclusively on professional displacement. Their responses focus on whether students can trust, evaluate and use AI-generated material responsibly and whether current forms of assessment remain valid.

The survey does not demonstrate that AI actually causes dishonest behaviour or reduced critical thinking. These findings measure professional concern and perceived risk. However, such perceptions are themselves important because they can influence teachers' willingness to adopt AI and their expectations regarding institutional governance.

3.3.9. Relationship between training and teaching practices

The detailed analysis shows that teachers who had participated in university-organised training reported stronger AI integration across several dimensions.

Table 3.20. Selected indicators according to previous university AI training

Indicator	**Trained teachers, % (N = 474)**	**Teachers without training, % (N = 486)**
Use AI often or always	54.4	42.4
Describe their knowledge as advanced	9.3	4.5
Use paid AI tools	35.4	19.5
Report that institutional guidelines exist	67.7	30.5
Transfer general AI competences	78.5	50.0
Transfer field-specific AI competences	81.4	62.8
Use AI to support students with fewer opportunities	74.3	51.9
Satisfied with their use of AI	66.0	50.8
Believe AI helps students learn better	51.7	36.2
Believe AI improves overall teaching and learning	62.0	47.1

Teachers with previous training were more likely to use AI frequently, report advanced knowledge, transfer competences, support accessibility and express satisfaction with their own practice.

The largest difference concerned the transfer of general AI competences: 78.5% among trained teachers compared with 50.0% among those without training. Differences were also substantial for accessibility and perceived institutional guidance.

These results are consistent with the view that training may be associated with more developed teaching practice. However, no causal relationship can be established. Teachers who are already interested in AI or who work in more supportive institutions may be more likely to participate in training. University context, discipline, access to tools and prior experience may all contribute to the observed differences.

The findings nevertheless provide a strong empirical rationale for making teacher training a central component of EduCATIA and for evaluating whether training is subsequently translated into observable teaching and student-learning outcomes.

3.3.10. Selected differences between countries and institutions

The teacher sample was highly concentrated in Kazakhstan and Uzbekistan, but the two national groups displayed different patterns.

Among teachers reporting Kazakhstan as their country of activity:

- 35.2% used AI often or always;
- 52.9% had attended university training;
- 50.2% reported institutional guidelines;
- 76.4% transferred field-specific competences;
- 55.4% were satisfied with their use of AI.

Among teachers reporting Uzbekistan:

- 86.3% used AI often or always;
- 42.6% had attended university training;
- 48.2% reported institutional guidelines;
- 62.7% transferred field-specific competences;
- 67.1% were satisfied with their use of AI.

The higher frequency of use in the Uzbekistan sample did not correspond to higher levels of formal training or competence transfer. Conversely, the Kazakhstan sample reported more training and field-specific transfer despite less frequent use.

These results should not be interpreted as independent national effects. The national samples are strongly shaped by their institutional and disciplinary composition. The Kazakhstan sample is dominated by a large medical university, whereas the Uzbekistan sample includes a substantial proportion of respondents from pedagogical institutions.

The institutional results confirm this heterogeneity.

Table 3.21. Selected teacher indicators by university

University	Valid N	Use AI often or always, %	Attended AI training, %	Guidelines exist, %	Transfer general competences, %	Transfer field-specific competences, %	Satisfied with AI use, %
Asfendiyarov Kazakh National Medical University	592	36.0	51.2	50.0	67.1	76.5	55.7
Tashkent State Pedagogical University	200	85.5	38.0	43.5	53.0	58.0	64.0
Yangi Asr University	43	90.7	62.8	72.1	76.7	81.4	79.1

Note: Astana IT University, Sapienza University of Rome and the University of Freiburg are not included because their teacher samples were too small for meaningful institutional comparison. The Yangi Asr result should also be interpreted cautiously because it is based on 43 respondents.

Asfendiyarov Kazakh National Medical University showed a comparatively lower frequency of use but higher field-specific competence transfer than Tashkent State Pedagogical University. Yangi Asr University reported high values across several indicators, but its substantially smaller sample limits the robustness of comparison.

These differences should be used to identify different institutional profiles and needs, not to construct a ranking. No adjustment was made for differences in discipline, age, gender, language or institutional role.

3.3.11. Differences by academic field, age and gender

Medicine was the largest declared faculty category, with 553 teachers, followed by other areas with 214 and education with 109.

Teachers in medicine reported relatively low frequent use of AI, at 32.9%, but relatively high participation in training, at 53.2%. A total of 83.9% wanted to acquire further field-specific competences, and 75.6% stated that they transferred such competences to students.

Teachers in education reported more frequent use, at 77.1%, and higher satisfaction, at 72.5%. Training participation was somewhat lower, at 44.0%, while 74.3% reported transferring field-specific competences.

This indicates different patterns of development:

- in medicine, use was less intensive, but demand for discipline-specific learning and reported competence transfer were high;
- in education, practical adoption and satisfaction were higher, although formal training did not reach half of the group.

Teachers in psychology reported frequent use in 82.6% of cases, but this result was based on only 46 respondents. Their reported transfer of field-specific competence was lower, at 47.8%, and only 34.8% reported using AI to improve accessibility for students with fewer opportunities. These results may indicate a specific training need, but the subgroup is too small for strong conclusions.

The computer science group contained only 12 teachers. Its high percentages should not be interpreted as stable disciplinary estimates.

Age-related differences were visible in frequency of use. AI was used often or always by:

- 36.6% of teachers born in or before 1960;
- 42.7% of those born between 1961 and 1970;
- 45.2% of those born between 1971 and 1980;
- 50.2% of those born between 1981 and 1990;
- 59.5% of those born between 1991 and 2000.

Advanced self-perceived knowledge was also less common in the oldest group, at 1.2%, compared with 9.8% among teachers born between 1991 and 2000.

However, interest in further field-specific learning remained high across age groups, including 89.0% among teachers born in or before 1960. The findings therefore do not support the assumption that older teachers are uninterested in AI. They suggest lower current use and self-perceived knowledge but strong willingness to learn.

Gender differences were generally limited. AI was used often or always by 51.4% of male and 47.5% of female teachers. Female teachers were somewhat more likely to report university training, at 51.2% compared with 43.5%, and field-specific competence transfer, at 74.3% compared with 64.5%.

Women also reported slightly greater concern about dishonest practices and reliability.

Selected subgroup differences were assessed statistically using the revised teacher dataset. Tests were limited to comparisons explicitly interpreted in the text in order to reduce the risk of multiple testing. Pearson chi-square tests were used for binary indicators, accompanied by Cramér's V, while Spearman's rank correlation was used for associations between ordered age groups and the full ordinal scales of AI-use frequency and self-perceived knowledge. Holm adjustment was applied within each family of comparisons.

For academic-field comparisons, the confirmatory analysis was restricted to medicine, education, psychology and other areas, each of which contained at least 40 respondents (combined $N = 922$). Biomedical sciences and computer science were retained as exploratory descriptive categories because their samples were too small for stable confirmatory comparisons. Significant field differences were found for frequent AI use, $\chi^2(3) = 131.43$, adjusted $p < 0.001$, Cramér's $V = 0.378$; participation in university AI training, $\chi^2(3) = 11.32$, adjusted $p = 0.020$, $V = 0.111$; interest in field-specific learning, $\chi^2(3) = 15.49$, adjusted $p = 0.006$, $V = 0.130$; field-specific competence transfer, $\chi^2(3) = 20.49$, adjusted $p < 0.001$, $V = 0.149$; use of AI for accessibility, $\chi^2(3) = 22.60$, adjusted $p < 0.001$, $V = 0.157$; and satisfaction, $\chi^2(3) = 14.61$, adjusted $p = 0.007$, $V = 0.126$. The largest association concerned frequency of use. No significant field difference was found in concern about the reliability of AI-generated information, $\chi^2(3) = 1.05$, adjusted $p = 0.789$, $V = 0.034$.

Post-hoc comparisons indicated that teachers in medicine reported significantly less frequent AI use than teachers in education, psychology and other areas. Psychology teachers reported significantly lower field-specific competence transfer than teachers in medicine and education, and lower accessibility-related use than the other principal groups. Satisfaction was significantly higher in education than in medicine. The remaining differences were smaller or did not remain significant after adjustment.

Age was weakly but significantly associated with AI-use frequency, Spearman's $\rho = 0.121$, $p < 0.001$, and with self-perceived AI knowledge, $\rho = 0.197$, $p < 0.001$, with younger groups tending to report greater use and knowledge. By contrast, age was not associated with interest in further field-specific learning, $\rho = 0.015$, $p = 0.650$. This supports the interpretation that older teachers report lower current use and knowledge but not lower willingness to develop their competences.

Gender differences were limited. After adjustment for the five gender comparisons, only field-specific competence transfer remained statistically significant: 74.3% among women and 64.5% among men, $\chi^2(1) = 7.93$, adjusted $p = 0.024$, Cramér's $V = 0.091$. This effect was small. No statistically robust gender differences were found in frequent AI use, previous university training, concern about dishonest practices or concern about reliability.

These tests identify associations within the surveyed teacher sample, but they do not establish independent effects of academic field, age or gender. Country, university and discipline are strongly interconnected in the dataset, and no adjustment was made for this institutional composition. The results should therefore be interpreted as exploratory evidence of subgroup differences rather than as causal or population-representative estimates.

Source: EduCATIA revised teacher survey dataset, teacher questionnaire, selected questions 5, 7, 18, 20, 21, 25, 26, 30, 37 and 40. Total teacher sample N = 960; valid N varies according to the subgroup analysis.

3.3.12. Summary of the teacher results

The teacher results reveal a population with extensive practical exposure to AI, substantial interest in further development and a strong awareness of its pedagogical and ethical implications.

AI is used across translation, presentation design, assignment creation, data analysis, accessibility and the production of teaching resources. However, only a small minority consider themselves advanced users, and approximately half have received university training or report that institutional guidelines exist.

Teachers report considerable transfer of general and field-specific AI competences to students, although the questionnaire does not establish the content, depth or assessability of those competences. Accessibility is also an established area of practice, with almost two thirds using AI to support students with fewer opportunities.

Acceptance is selective. Teachers are most comfortable with AI supporting the creation of teaching content and more cautious when it is involved in assessment or student assignments.

Perceived benefits coexist with considerable concern. Fewer than half believe that AI directly helps students learn faster or better, while strong majorities are concerned about reliability, dishonest practices and the effects on critical thinking.

The detailed analysis also indicates that previous university training is associated with more frequent use, stronger competence transfer, greater use for accessibility and higher satisfaction. Although the data do not establish causality, this pattern supports the prioritisation of structured and continuing teacher development within EduCATIA.

Overall, teacher adoption is already widespread, but the quality and institutional maturity of that adoption remain uneven. The principal challenge is not merely to increase use, but to strengthen teachers' capacity to design, supervise, explain and evaluate AI-supported learning in a critical, ethical, inclusive and discipline-specific manner.

Source: EduCATIA revised teacher survey dataset and teacher tables prepared by Simona Perone, teacher questionnaire, questions 7–40, valid N = 960.

Methodological note: The teacher-specific revised dataset includes the additional verified response from the University of Freiburg. It should be merged into the project's master final dataset before publication so that the methodology, overview tables and all source notes use the same teacher denominator. Percentages for Likert-type items combine "mostly agree" and "strongly agree". Subgroup analyses are descriptive and unweighted.

3.4. Comparison between students and teachers

The comparison between students and teachers provides a broader view of the stage reached by AI integration within the participating institutions. Both groups report widespread use and considerable interest in further learning. However, they differ in their perceptions of educational benefits, training needs, ethical acceptability and the possible effects of AI on students' learning and critical thinking.

The comparison must be interpreted with methodological caution. The student and teacher samples are independent rather than paired, and they differ in their national, institutional and disciplinary composition. Moreover, questions addressing similar topics were not always worded identically. Direct comparisons were therefore made only where the response formats and underlying meanings were sufficiently close. Other contrasts are presented as differences in perspective rather than as measurements of exactly the same phenomenon.

All comparisons are descriptive. No weighting or inferential statistical testing was applied.

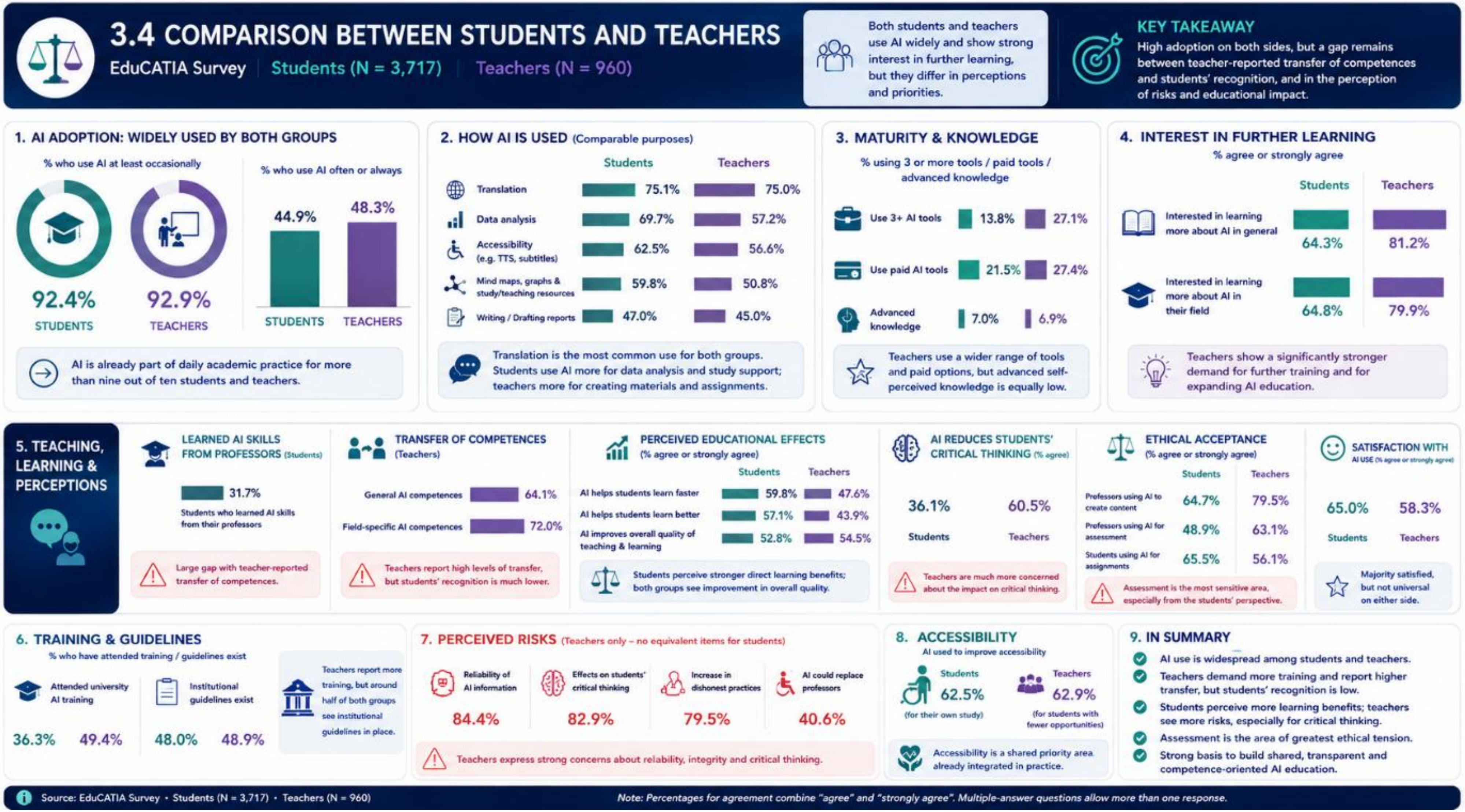

Figure 4. Comparison between teachers and students

3.4.1. AI adoption is similarly widespread in both groups

The general prevalence of AI use was almost identical among students and teachers. A total of 92.4% of students used AI for studying at least occasionally, compared with 92.9% of teachers who used it in their teaching.

Teachers were slightly more likely to report frequent use: 48.3% used AI often or always, compared with 44.9% of students. The difference of 3.4 percentage points is relatively modest and should not be interpreted as evidence of a substantial gap between the groups.

Table 3.22. Selected comparative indicators for students and teachers

Indicator	Students, %	Teachers, %	Difference in percentage points
Use AI at least occasionally	92.4	92.9	+0.5
Use AI often or always	44.9	48.3	+3.4
Use three or more AI tools	13.8	27.1	+13.3
Use paid AI tools	21.5	27.4	+5.9
Describe their knowledge as advanced	7.0	6.9	−0.1
Participated in university AI training	36.3	49.4	+13.1
Report that institutional guidelines exist	48.0	48.9	+0.9
Interested in learning more about AI in their field	64.8	79.9	+15.1

Population: students, valid N = 3,717; teachers, valid N = 960.

Note: A positive difference indicates a higher percentage among teachers. The questions on use and training refer respectively to students' study activities and teachers' teaching practices.

The similarity in general adoption indicates that AI is not confined to one side of the educational relationship. It is already used extensively by both those who teach and those who learn.

Nevertheless, the frequency indicator does not describe the quality, complexity or educational appropriateness of that use. Students and teachers may use AI often while relying primarily on general-purpose tools and relatively simple functions.

3.4.2. The two groups use AI for both common and role-specific purposes

Several AI uses were measured in sufficiently similar ways to permit comparison.

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Table 3.23. Comparable purposes of AI use

Comparable use	Students	Teachers	Difference	$\chi^2(1)$	p	Cramér's V
Translation	75,1%	75,0%	+0,1 pp	0,003	0,955	0,001
Data analysis	69,7%	57,2%	+12,5 pp	53,948	<0,001	0,107
Accessibility-related purposes	62,5%	56,6%	+6,0 pp	11,428	<0,001	0,049
Mind maps, graphs and resources	59,8%	50,8%	+8,9 pp	24,903	<0,001	0,073
Writing or drafting reports	47,0%	45,0%	+2,0 pp	1,260	0,262	0,016

Purpose	Students, %	Teachers, %
Translation	75.1	75.0
Data analysis	69.7	57.2
Accessibility-related purposes	62.5	56.6
Mind maps, graphs and study or teaching resources	59.8	50.8
Writing or drafting reports	47.0	45.0

Note: These were separate binary questions. Respondents could select several uses, and the percentages should not be added together. The accessibility and resource-production items were adapted to the academic role of each group and are therefore comparable in general meaning rather than identical in wording.

Pearson chi-square tests were used to compare the student and teacher samples for the five binary items whose content was sufficiently similar across the two questionnaires. A Bonferroni-adjusted significance threshold of $p < 0.01$ was applied to account for the five comparisons.

No statistically significant difference was found for translation, which was reported by 75.1% of students and 75.0% of teachers, $\chi^2(1, N = 4{,}677) = 0.003$, $p = 0.955$, Cramér's V = 0.001. Nor was the difference in writing or drafting reports statistically significant: 47.0% among students and 45.0% among teachers, $\chi^2(1, N = 4{,}677) = 1.260$, $p = 0.262$, Cramér's V = 0.016.

Students were significantly more likely than teachers to report using AI for data analysis, 69.7% compared with 57.2%, $\chi^2(1, N = 4{,}677) = 53.948$, $p < 0.001$, Cramér's V = 0.107. Significant differences were also observed for accessibility-related purposes, 62.5% compared with 56.6%, $\chi^2(1, N = 4{,}677) = 11.428$, $p < 0.001$, Cramér's V = 0.049, and for mind maps, graphs and study or teaching resources, 59.8% compared with 50.8%, $\chi^2(1, N = 4{,}677) = 24.903$, $p < 0.001$, Cramér's V = 0.073.

Although three differences were statistically significant, their effect sizes were small. The largest difference concerned data analysis, at 12.5 percentage points. Statistical significance should therefore not be interpreted automatically as evidence of a large or educationally decisive difference between the two populations.

Each questionnaire also contained role-specific uses. Tutoring, explanations and study support were reported by 78.7% of students but had no direct equivalent in the teacher questionnaire. Conversely, teachers were asked about the creation of presentations and assignments, reported by 63.4% and 61.9% respectively.

The results indicate that the same AI ecosystem supports different functions according to academic role. For students, AI frequently operates as a personal learning assistant. For teachers, it functions more often as a resource for instructional preparation and activity design.

3.4.3. Teachers use a broader range of tools, but advanced self-perceived knowledge is equally uncommon

Teachers reported a broader repertoire of AI tools. A total of 27.1% used three or more tools, compared with 13.8% of students. Teachers were also somewhat more likely to use paid tools: 27.4%, compared with 21.5%.

However, this broader tool use did not correspond to a higher proportion describing themselves as advanced. Advanced self-perceived knowledge was almost identical in the two groups: 7.0% among students and 6.9% among teachers.

The distribution of the remaining knowledge categories differed:

- 47.9% of students described their knowledge as intermediate, compared with 36.1% of teachers;
- 34.3% of students described it as basic, compared with 46.5% of teachers;
- approximately one in ten respondents in both groups reported no knowledge.

This difference may indicate greater caution among teachers when evaluating their own competence. Teachers may apply higher standards because they consider not only functional use but also their ability to explain, supervise and integrate AI pedagogically. Alternatively, students and teachers may interpret the categories differently.

Since the measure is self-reported, it cannot establish which group possesses greater objective competence. The strongest conclusion is that extensive use and the use of several tools do not automatically produce a self-perception of advanced AI knowledge.

3.4.4. Teachers express a stronger demand for further training

Both groups demonstrated substantial interest in further AI learning, but the demand was considerably stronger among teachers.

Interest in acquiring additional AI competences within the respondent's field was expressed by 79.9% of teachers and 64.8% of students, a difference of 15.1 percentage points. A similar pattern was found for general AI learning, with 81.2% of teachers and 64.3% of students expressing interest.

Teachers were also more supportive of expanding formal provision:

- 75.0% of teachers agreed that their university should increase the number of AI courses in their field, compared with 50.5% of students;
- 63.4% of teachers believed that universities should improve professors' AI competences, compared with 53.8% of students.

The stronger demand among teachers may reflect their dual responsibility. Teachers need to develop their own competence while also deciding how AI should be introduced, supervised and assessed in students' learning.

The difference should not be interpreted as a lack of student interest. Almost two thirds of students wanted further field-specific learning, which represents a substantial demand. Rather, the findings indicate that teachers perceive capacity development as an especially urgent professional need.

3.4.5. Teachers report greater access to training, while perceptions of guidelines are nearly identical

Almost half of the teachers, 49.4%, had participated in university-organised AI training, compared with 36.3% of students. Teachers therefore reported formal training 13.1 percentage points more frequently.

This difference is plausible given that institutional capacity-building initiatives may initially prioritise teaching staff. Nevertheless, formal provision had not reached approximately half of the teachers or almost two thirds of the students.

By contrast, perceptions of institutional guidelines were nearly identical:

- 48.0% of students reported that their university provided AI guidelines;
- 48.9% of teachers reported that institutional guidelines existed.

The convergence of these figures is notable. It suggests that approximately half of both groups recognise some form of institutional guidance, while the other half either work without such guidance or are unaware of it.

However, the separate questions on guideline clarity contained internal inconsistencies in both questionnaires. Some respondents who initially stated that no guidelines existed subsequently assessed their clarity, while others reported that guidelines existed but later selected the "no guidelines" option.

The comparison therefore supports a general conclusion about limited visibility of institutional guidance, but it does not justify treating the two clarity variables as precise and fully consistent measurements of governance quality.

3.4.6. There is a substantial difference between reported teaching transfer and students' recognition of learning

The most important comparative contrast concerns the transfer of AI competences.

Among teachers:

- 64.1% stated that they transferred general AI competences to students;
- 72.0% stated that they transferred field-specific AI competences.

Among students, only 31.7% reported that they had learned AI skills from their professors.

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These questions do not measure the same interaction directly. The students and teachers were not linked at course level, and the wording differs. Teachers reported whether they believed they transferred competences, whereas students reported whether they recognised that they had learned such competences from their professors.

The results should therefore not be interpreted as proof that teachers overestimated their activity or that students failed to recognise effective instruction. Nevertheless, the size of the difference is analytically important.

The questionnaire did not measure the intermediate processes through which teacher activity becomes a competence explicitly recognised by students. The observed discrepancy may arise when AI is used or demonstrated informally during teaching, when the intended competence is not formulated as an explicit learning outcome, when students have limited opportunities to practise and receive feedback, or when the competence is not assessed or clearly identified as AI-related learning.

These are possible interpretative mechanisms rather than separately measured survey indicators, and no percentages can be assigned to them from the available data. The questionnaire cannot determine which mechanism contributes most strongly to the observed difference. The direct empirical finding is therefore limited to the contrast between teacher-reported competence transfer and student-recognised learning, taking into account that the two questions were worded differently and that the student and teacher respondents were not linked at course level.

3.4.7. Ethical acceptance varies according to both purpose and academic role

The questionnaires included three related scenarios: AI-assisted content or material creation, AI-assisted assessment and students' use of AI for assignments.

Table 3.24. Ethical acceptance of selected AI uses

AI use considered fair	**Students, %**	**Teachers, %**
Professors or teachers using AI to create educational content or materials	64.7	79.5
Professors or teachers using AI to assess students' competences	48.9	63.1
Students using AI to complete assignments	65.5	56.1

Teachers were more accepting than students of teachers' use of AI. The difference was 14.8 percentage points for content creation and 14.2 points for assessment.

Students, by contrast, were more accepting of their own use of AI for assignments. A total of 65.5% considered this fair, compared with 56.1% of teachers.

This pattern reveals a role-based asymmetry:

- teachers show greater confidence in AI when it supports their own professional activities;
- students show greater acceptance when AI supports student work;

- both groups are more cautious when AI is involved in assessing competence than when it is used to create content or complete tasks.

Assessment remains the most sensitive area, particularly from the student perspective. Fewer than half of the students accepted professors' use of AI in assessment, despite a majority of teachers considering it fair.

The questionnaire did not specify whether AI would make autonomous decisions or merely support human judgement. Nor did it refer to transparency, disclosure or the possibility of contesting an AI-supported evaluation. These conditions may substantially affect acceptance.

3.4.8. Students perceive stronger direct learning benefits, while teachers perceive greater cognitive risk

Students evaluated the direct effects of AI on learning more positively than teachers.

Table 3.25. Perceived educational effects of AI

Statement	**Students agreeing, %**	**Teachers agreeing, %**
AI helps students learn faster	59.8	47.6
AI helps students learn better	57.1	43.9
AI improves the overall quality of teaching and learning	52.8	54.5
AI reduces students' critical thinking	36.1	60.5

Students were 12.2 percentage points more likely to report that AI helped them learn faster and 13.2 points more likely to report that it helped them learn better.

By contrast, the two groups produced very similar evaluations of the overall quality of teaching and learning. Agreement was 52.8% among students and 54.5% among teachers.

This combination suggests that teachers may recognise system-level benefits—such as improved materials, accessibility or teaching organisation—while remaining more cautious about direct effects on individual learning.

The largest difference concerned critical thinking. Only 36.1% of students agreed that AI had reduced their own critical thinking, compared with 60.5% of teachers who believed that AI reduced students' critical thinking.

The wording must be considered carefully:

- students evaluated their own experience;
- teachers evaluated an effect on students more generally.

Teachers also responded to a separate risk question in which 82.9% expressed concern about the impact of AI on students' critical thinking. There was no directly equivalent student question.

The evidence therefore reveals a clear difference in perspective, but it cannot determine which perception is more accurate. Students may underestimate effects on their own cognitive independence, while teachers may generalise from particularly visible cases or from professional concerns. Objective measures of critical thinking would be required to establish whether and under which conditions AI produces a negative effect.

3.4.9. Accessibility is a shared area of practical use

Accessibility-related AI use was reported by substantial proportions of both groups:

- 62.5% of students used AI for accessibility-related purposes, including text-to-speech and subtitles;
- 56.6% of teachers used AI to improve lesson accessibility;
- 62.9% of teachers stated that they used AI to support students with fewer opportunities.

Although the items are not identical, they point to a shared recognition of AI's potential to reduce linguistic, sensory and educational barriers.

The findings are particularly relevant because they concern existing use rather than only hypothetical interest. Students and teachers are already experimenting with AI-supported accessibility.

However, the survey does not establish whether these tools comply with formal accessibility standards, protect personal data or respond to needs identified by the students concerned. Reported use should therefore be interpreted as a promising area of practice rather than as evidence of fully validated inclusive provision.

3.4.10. Satisfaction is higher among students, but the objects of evaluation differ

A total of 65.0% of students reported satisfaction with the use of AI in their degree programme. Among teachers, 58.3% were satisfied with their own use of AI in teaching.

The difference of 6.7 percentage points should not be treated as a direct comparison because the two groups evaluated different objects:

- students evaluated the presence and use of AI within their programme;
- teachers evaluated their own teaching practice.

Nevertheless, both indicators show that satisfaction is positive but not universal. A considerable proportion of both groups remain dissatisfied or uncertain about the current quality of AI integration.

The more detailed analyses showed that satisfaction was higher where respondents reported training, curriculum integration or more visible teacher use. This pattern supports the interpretation that satisfaction depends not simply on access to AI tools but on the quality and structure of their educational use.

3.4.11. Teachers identify risks more strongly than students

The teacher questionnaire included a broader set of risk indicators than the student questionnaire. Strong majorities of teachers expressed concern about:

- reliability of AI-generated information: 84.4%;
- effects on students' critical thinking: 82.9%;

- increased dishonest practices: 79.5%;
- replacement of professors: 40.6%.

The student questionnaire did not contain directly equivalent questions on reliability, dishonesty or teacher replacement. Consequently, a complete student–teacher comparison of risk perception is not possible.

The available evidence nevertheless shows that teachers approach AI through a more risk-conscious professional perspective. They must consider the reliability of educational content, academic integrity, assessment validity and responsibility for student learning. Students are more directly exposed to the practical benefits of speed, explanation and personalised support.

These perspectives are not mutually exclusive. The comparative findings indicate that educational AI policy must address both:

- the benefits students experience in everyday learning;
- the risks teachers perceive in relation to quality, integrity and cognitive development.

3.4.12. Comparative interpretation

The comparison reveals a shared environment of high adoption but uneven educational maturity.

Students and teachers converge in several respects:

- more than nine out of ten use AI at least occasionally;
- advanced self-perceived knowledge is limited to approximately 7%;
- about half recognise the existence of institutional guidelines;
- both groups use AI extensively for translation and accessibility;
- both groups support further development of AI-related education;
- neither group expresses unconditional acceptance of every AI application.

However, several role-related differences emerge:

1. **Teachers use a wider range of tools**, but do not perceive themselves as more advanced than students.
2. **Teachers express a stronger demand for training and curriculum expansion**, reflecting their responsibility for integrating AI into teaching.
3. **Students perceive stronger direct learning benefits**, particularly faster and better learning.
4. **Teachers perceive substantially greater risks**, especially for critical thinking, reliability and academic integrity.
5. **Teachers are more accepting of AI in their own professional activities**, whereas students are more accepting of AI in student assignments.
6. **A large perception gap exists in competence transfer**, with teachers reporting considerably more transfer than students report learning from professors.

7. **Assessment is the area of greatest tension**, particularly because teachers are more willing than students to accept AI-assisted assessment.

The comparison therefore does not support a simple division between enthusiastic students and resistant teachers. Both populations combine adoption, interest, perceived benefits and concern, but they assess these dimensions from different positions within the educational process.

Students primarily experience AI as a tool for immediate learning support, productivity and access. Teachers must additionally consider instructional design, assessment validity, professional responsibility, academic integrity and the long-term development of students' competences.

The central comparative conclusion is that the next stage of AI integration should connect these two perspectives. Widespread student use must be accompanied by explicit teaching guidance, while teachers' professional concerns must be translated into transparent practices that students can understand and recognise as part of their learning.

Source: EduCATIA revised survey tables prepared by Simona Perone, student questionnaire, valid N = 3,717; teacher questionnaire, valid N = 960.

Methodological note: Percentages for four-point agreement scales combine "mostly agree" and "strongly agree". Comparisons are descriptive and unweighted. Questions were compared only where their content and response structures were sufficiently similar; contrasts based on differently worded questions are explicitly qualified.

3.5. Differences by country, university and academic area

The disaggregated tables prepared for students and teachers make it possible to examine whether the general findings are distributed uniformly across countries, institutions and academic areas. The results show substantial variation, particularly in the frequency of AI use, participation in training, competence transfer, curriculum integration and satisfaction.

These differences must not be interpreted as direct effects of country, university or discipline. The three dimensions are strongly interconnected within the sample. Particular universities are concentrated in one country and often specialise in a limited number of academic fields. Differences attributed to a country may therefore reflect the institutional and disciplinary composition of its respondents.

The comparisons are descriptive and unweighted. They are intended to identify different profiles of AI adoption and institutional readiness rather than to rank countries, universities or academic fields.

3.5.1. Differences by country

Country-level analysis focuses primarily on Kazakhstan and Uzbekistan, which together account for the large majority of both samples. The student samples from Germany and Italy and the teacher samples from European countries are too small and institutionally heterogeneous to support balanced national comparisons.

For this reason, the European responses are not treated as a benchmark against which Kazakhstan and Uzbekistan are assessed. An exploratory examination of the 104 students reporting Italy shows a mixed profile rather than a consistent European advantage. Frequent AI use was almost identical to that observed in Kazakhstan and Uzbekistan combined, at 44.2% and 45.3% respectively. Italian respondents reported less university AI training, lower awareness of guidelines and lower satisfaction with AI integration, but substantially greater interest in field-specific AI learning and stronger demand for additional AI courses and improved teacher competences.

These results may reflect differences in institutional expectations, academic composition, questionnaire context or critical awareness, but the survey cannot distinguish among these explanations. They should not be interpreted as evidence that either geographical context possesses a more advanced higher education system. The Italian figures are therefore used only as exploratory contextual evidence. The German subsample is not used for comparative interpretation because of its small size and inconsistencies between reported country and institutional affiliation.

Student results by country

The general frequency of AI use was very similar among students in Kazakhstan and Uzbekistan. AI was used often or always by 44.6% of students reporting Kazakhstan and 45.8% of those reporting Uzbekistan.

Participation in training and awareness of institutional guidelines were also almost identical. Approximately 36% of students in both countries had attended university AI training during the previous two years, while around half reported that institutional guidelines existed.

Greater differences emerged in relation to curriculum integration, competence transfer and demand for discipline-specific learning.

Table 3.26. Selected student indicators by country

Indicator	**Kazakhstan, % (N = 1,587)**	**Uzbekistan, % (N = 1,938)**
Use AI often or always	44.6	45.8
Describe their AI knowledge as advanced	8.5	5.8
Attended university AI training	36.2	36.4
Report that institutional guidelines exist	49.1	47.4
Learned AI skills from professors	22.1	38.4
Degree includes field-specific AI teaching	28.4	37.9
Interested in learning more about AI in their field	78.0	54.1
Satisfied with AI use in their degree programme	61.4	69.3

Students in the Kazakhstan sample expressed considerably greater interest in acquiring AI competences related to their field: 78.0%, compared with 54.1% in Uzbekistan. At the same time, they were less likely to report having learned AI skills from professors or to identify field-specific AI teaching within their degree programme.

This combination points to a particularly visible gap between demand and formal provision in the Kazakhstan student sample. Interest in discipline-specific AI learning was high, but recognised competence transfer and curriculum integration were comparatively limited.

Students in Uzbekistan were more likely to report learning AI skills from professors, field-specific curriculum provision and satisfaction with the use of AI in their programme. Nevertheless, only a minority reported formal integration, meaning that considerable scope for development remains in both countries.

The national comparison is strongly influenced by academic composition. Medicine represents 89.4% of the Kazakhstan student sample, whereas education represents 65.2% of the Uzbekistan sample and other academic areas a further 31.1%. The results cannot therefore distinguish clearly between country-level and disciplinary differences.

Teacher results by country

The teacher results show a more pronounced contrast between the two principal country groups.

Table 3.27. Selected teacher indicators by country

Indicator	**Kazakhstan, % (N = 679)**	**Uzbekistan, % (N = 249)**
Use AI often or always	35.2	86.3
Attended university AI training	52.9	42.6
Report that institutional guidelines exist	50.2	48.2
Transfer field-specific AI competences	76.4	62.7
Use AI to support students with fewer opportunities	67.5	52.6
Interested in learning more about AI in their field	83.2	69.5
Satisfied with their use of AI in teaching	55.4	67.1
Concerned about the reliability of AI information	83.7	85.5

Teachers in Uzbekistan reported much more frequent use of AI: 86.3% used it often or always, compared with 35.2% in Kazakhstan. They were also more satisfied with their current use.

However, teachers in Kazakhstan were more likely to have attended university training, transfer field-specific competences and use AI to support students with fewer opportunities. They also expressed stronger interest in acquiring additional discipline-specific competences.

Awareness of institutional guidelines was almost identical in the two groups, at approximately half of the respondents. Concern about the reliability of AI-generated information was also very high in both countries.

The pattern demonstrates that frequent use does not necessarily correspond to stronger formal support or competence transfer. The Uzbekistan teacher sample shows a profile of high practical adoption, whereas the Kazakhstan sample reports more training and a greater transfer of field-specific competence despite less frequent use.

These differences are again closely related to institutional and disciplinary composition. Medicine represents 80.4% of the Kazakhstan teacher sample. In Uzbekistan, the sample is more diverse: 42.2% teach in other areas, 35.7% in education and 14.9% in psychology. In addition, 86.3% of teachers reporting Kazakhstan belong to Asfendiyarov Kazakh National Medical University, while 80.3% of those reporting Uzbekistan belong to Tashkent State Pedagogical University.

Country and university effects therefore cannot be separated using these descriptive data.

3.5.2. Differences by university

The institutional analysis reveals different combinations of practical adoption, training, governance, curriculum integration and satisfaction.

Only institutions with sufficiently large samples are included in the main comparative tables. "Other institutions" is excluded because it combines several organisations and cannot be interpreted as a single institutional context.

Student results by university

Table 3.28. Selected student indicators by university

University	N	Use AI often or always, %	AI training, %	Reported awareness of AI guidelines, %	Learned skills from professors, %	Field-specific AI teaching, %	Interest in field-specific learning, %	Satisfied, %
Asfendiyarov Kazakh National Medical University	1,025	40.3	26.1	42.0	24.1	27.5	76.4	59.8
Astana IT University	148	57.4	34.5	52.7	33.1	43.9	64.9	69.6
Tashkent State Pedagogical University	1,460	48.0	39.2	50.0	39.4	39.5	55.7	71.5
Yangi Asr University	194	40.2	22.7	38.7	33.0	28.9	49.0	62.9

Astana IT University reported the highest proportion of students using AI often or always and the highest level of field-specific AI teaching among the institutions shown. This profile is consistent with its technological orientation, although the sample is considerably smaller than those of the two largest universities.

Tashkent State Pedagogical University showed the highest participation in training, the highest proportion learning AI skills from professors and the highest satisfaction. Approximately four in ten students reported field-specific AI teaching, which was above the overall student average but still indicates that most respondents did not recognise such provision.

Asfendiyarov Kazakh National Medical University showed a different profile. Student interest in field-specific AI learning was very high, at 76.4%, but only 27.5% reported corresponding curriculum provision and 24.1% reported learning AI skills from professors. Training participation was also comparatively low. This constitutes one of the clearest institutional examples of unmet demand.

Yangi Asr University reported comparatively low training participation, awareness of guidelines and field-specific interest. However, almost two thirds of respondents were satisfied with the current use of AI, demonstrating that satisfaction does not depend solely on the amount of formal provision reported.

Sapienza University of Rome, with 60 student respondents, and the University of Freiburg, with 13, were not included in the comparative table. Their results can be reported descriptively in an annex but should not be used for institutional ranking.

Teacher results by university

Table 3.29. Selected teacher indicators by university

University	N	Use AI often or always, %	AI training, %	Reported awareness of AI guidelines, %	Transfer field-specific competences, %	AI for students with fewer opportunities, %	Interest in field-specific learning, %	Satisfied, %
Asfendiyarov Kazakh National Medical University	592	36.0	51.2	50.0	76.5	66.7	82.8	55.7
Tashkent State Pedagogical University	200	85.5	38.0	43.5	58.0	48.5	66.0	64.0
Yangi Asr University	43	90.7	62.8	72.1	81.4	67.4	86.0	79.1

The institutional profiles among teachers broadly reproduce the country-level contrast.

At Asfendiyarov Kazakh National Medical University, frequent use was comparatively low, but training participation, field-specific competence transfer and accessibility-related use were relatively strong. Interest in additional field-specific learning was also high.

The finding that 50.0% of the 592 surveyed teachers at Asfendiyarov Kazakh National Medical University reported that guidelines existed should not be interpreted as confirmation that a formal university-wide policy was in force. Positive responses were concentrated among teachers with greater exposure to AI-related institutional or professional activities. Guidelines were reported by 67.7% of teachers who had participated in university-organised AI training, compared with 31.5% of those without such training. Awareness also increased from 16.7% among teachers who never used AI to 71.6% among those who used it often and 83.8% among those who used it always.

A comparable pattern was found among students. At the same institution, 42.0% reported that guidelines existed, but the proportion reached 81.0% among students who had attended AI training, compared with 28.1% among those without training. Positive responses were also substantially more common among students who perceived that the university provided general or field-specific AI competences.

These associations suggest that respondents may have interpreted training instructions, faculty- or course-level rules, or other forms of local guidance as institutional guidelines. Internal inconsistencies support this interpretation: some respondents who initially reported that guidelines existed subsequently selected the “no guidelines” option, while others who initially reported that they did not exist nevertheless assessed them as clear. The result therefore indicates uneven visibility and differing interpretations of guidance within the institution rather than establishing its formal administrative status.

Source: EduCATIA final survey dataset, Asfendiyarov Kazakh National Medical University, students’ and teachers’ questions 21–23; students, valid N = 1,025; teachers, valid N = 592.

Tashkent State Pedagogical University displayed very high practical adoption but lower formal training, guideline awareness, competence transfer and accessibility-related use. The result suggests that widespread use may be developing faster than the institutional and pedagogical structures required to support it.

Yangi Asr University recorded high values across most indicators, including use, training, guidelines, transfer and satisfaction. However, the sample contains only 43 teachers and should therefore be interpreted cautiously.

The results do not establish that one institution is more advanced overall. Rather, they identify at least three different institutional profiles:

1. **High demand and competence transfer, but less frequent use**, as observed among the Asfendiyarov teacher sample.
2. **High practical adoption, but weaker formal structuring**, as observed among the Tashkent State Pedagogical University teacher sample.
3. **High adoption combined with comparatively strong institutional support**, as suggested by the smaller Yangi Asr University sample.

Astana IT University, Sapienza University of Rome and the University of Freiburg had teacher samples of 13, 12 and 1 respectively. Their percentages are not sufficiently stable for institutional comparison.

3.5.3. Differences by students' academic area

Academic-field comparisons are particularly important for EduCATIA because the relevance, risks and professional applications of AI differ across disciplines.

Table 3.30. Selected student indicators by academic area

Academic area	N	Use AI often or always, %	AI training, %	Learned skills from professors, %	Field-specific AI teaching, %	Interest in field-specific learning, %	Satisfied, %
Medicine	1,469	43.2	36.0	21.8	27.4	78.4	60.0
Education	1,291	48.6	40.9	41.3	41.2	55.1	71.1
Other areas	745	42.4	26.4	32.2	30.1	57.4	61.9
Computer science	93	60.2	32.3	26.9	45.2	72.0	75.3
Psychology	68	47.1	33.8	33.8	32.4	66.2	60.3
Biomedical sciences	51	7.8	84.3	74.5	84.3	15.7	84.3

Medicine and education are the only areas with sufficiently large samples for relatively robust comparison.

Education students reported more frequent use, greater participation in training, more competence acquisition through professors and more field-specific curriculum provision than medical students. Satisfaction was also higher in education.

Medical students, however, expressed much greater interest in acquiring AI competences within their field: 78.4%, compared with 55.1% among education students. This difference reinforces the interpretation that medical students experience a substantial unmet demand for discipline-specific provision.

The medical profile is particularly important for EduCATIA. Students show strong interest in AI applications within their future profession, but fewer than three in ten report field-specific AI teaching, and only around one in five report learning AI competences from professors.

Education students report greater exposure and competence transfer, but the results still indicate that fewer than half recognise field-specific AI provision. Furthermore, only 43.8% of education students agreed that AI improved the quality of teaching and learning, compared with 63.3% of medical students. Greater curriculum exposure does not therefore imply uniformly stronger confidence in educational benefits.

The computer science subgroup reported the highest frequent use, at 60.2%, and comparatively high field-specific integration and satisfaction. However, only four of its 93 respondents described their knowledge as advanced. This demonstrates that disciplinary proximity to technology should not be assumed to produce advanced AI competence automatically.

The psychology subgroup showed moderate use and interest but relatively limited formal integration. Given the ethical sensitivity of psychological assessment, mental-health applications and personal data, the small sample should be treated as exploratory rather than conclusive.

The biomedical sciences subgroup produced an unusually distinctive response profile: very low frequent use, but very high training, guideline awareness, competence transfer and curriculum integration, together with low interest in further field-specific learning. The group contains only 51 students and is strongly concentrated in particular national and linguistic contexts. These results require verification before being interpreted as a substantive disciplinary pattern.

Accessibility-related use also varied across fields. It was reported by 67.4% of education students and 55.8% of medical students. The particularly high result in education is consistent with the relevance of adaptive materials, translation, subtitles and support for students with different learning needs.

3.5.4. Differences by teachers' academic area

The teacher questionnaire recorded academic area through both a closed faculty question and an open-ended question about the subject taught. The closed faculty variable provides the most direct comparison with the student questionnaire and the priority areas of EduCATIA.

Table 3.31. Selected teacher indicators by declared faculty

Academic area	N	Use AI often or always, %	AI training, %	Transfer field-specific competences, %	AI for students with fewer opportunities, %	Interest in field-specific learning, %	Satisfied, %
Medicine	553	32.9	53.2	75.6	65.6	83.9	53.3
Other areas	214	64.0	44.9	66.4	57.0	73.8	60.3
Education	109	77.1	44.0	74.3	69.7	74.3	72.5
Psychology	46	82.6	32.6	47.8	34.8	69.6	58.7
Biomedical sciences	26	42.3	46.2	61.5	65.4	80.8	69.2
Computer science	12	100.0	75.0	100.0	83.3	91.7	100.0

Teachers in medicine reported the lowest frequent use among the three larger faculty groups, but more than half had received university training, and three quarters reported transferring field-specific competences. Interest in further learning was especially high.

This pattern suggests that medical teachers may approach AI more cautiously or selectively, while recognising its professional relevance and the need to transfer related competences. Such caution may reflect the importance of reliability, patient safety, data protection and human oversight, although the survey cannot establish the reasons directly.

Teachers in education reported substantially more frequent use, high competence transfer, strong accessibility-related use and comparatively high satisfaction. This profile is consistent with the broad range of potential educational applications, including material creation, adaptive support, assessment and learning analytics.

Psychology teachers reported very frequent use, but comparatively low participation in training, field-specific competence transfer and use for accessibility. This combination may indicate a gap between adoption and structured professional integration. However, the subgroup contains only 46 respondents, and the results should be treated as exploratory.

The biomedical sciences and computer science samples are too small for reliable comparisons. In particular, the very high percentages in computer science are based on only 12 respondents and should not be presented as representative of the field.

Concern about the reliability of AI-generated information was high across all major academic areas: 83.9% in medicine, 87.2% in education, 87.0% in psychology and 83.6% in other areas. Reliability therefore emerges as a transversal issue rather than a concern confined to health-related disciplines.

3.5.5. Additional analysis based on the subjects taught

Simona Perone's classification of teachers' open-ended descriptions of the subjects they teach provides a complementary disciplinary perspective. This classification should not be treated as identical to the faculty variable because it was constructed retrospectively from free-text responses.

The following table includes only classified subject groups with at least 50 respondents.

Table 3.32. Selected teacher indicators by classified teaching subject

Classified subject area	N	Use AI often or always, %	AI training, %	Transfer field-specific competences, %	AI for students with fewer opportunities, %	Satisfied, %
Medicine and health sciences	502	33.9	51.4	74.9	65.7	52.6
Education, psychology and social sciences	96	72.9	44.8	63.5	51.0	55.2
Languages and literature	93	59.1	53.8	82.8	77.4	78.5
Other or multidisciplinary subjects	79	64.6	46.8	68.4	53.2	60.8

Humanities, law and arts	60	65.0	36.7	63.3	56.7	61.7

The subject-based classification confirms the comparatively low frequency of use among teachers in medicine and health sciences, alongside high interest and competence transfer.

It also identifies languages and literature as an area with comparatively strong competence transfer, accessibility-related use and satisfaction. Translation and multilingual support are likely to be particularly relevant within this group, although the questionnaire does not provide sufficient detail to establish which specific applications account for the pattern.

The broader education, psychology and social-sciences category showed high practical use but more moderate competence transfer and accessibility-related use. This combined category includes heterogeneous subjects and should not replace the separate faculty analysis.

3.5.6. Overall interpretation of subgroup differences

The disaggregated analysis does not reveal a single progression from low to high AI maturity. Instead, countries, universities and academic areas display different combinations of adoption, training, institutional support and competence transfer.

Four broad patterns emerge:

1. **High use with limited formal structuring.**

This profile is particularly visible among teachers from Tashkent State Pedagogical University, where AI use is very frequent, but training, guidelines and competence transfer are comparatively less widespread.

2. **Strong demand with insufficient curriculum integration.**

This pattern is especially evident among medical students and students from Asfendiyarov Kazakh National Medical University.

3. **More structured provision without universally intensive use.**

Some groups report relatively strong training and competence transfer despite less frequent use, particularly teachers in medicine.

4. **High adoption accompanied by stronger institutional support.**

This pattern appears in some smaller samples, including Yangi Asr University and selected technological or language-related groups, but their limited size requires caution.

The findings demonstrate that EduCATIA should not apply a uniform capacity-building model to every institution or academic field. Some contexts require basic institutional guidance and formalisation of existing practices; others require advanced discipline-specific content, assessment redesign, or mechanisms for making teacher competence transfer more explicit and recognisable to students.

The most robust comparative conclusion is not that one country, institution or discipline is categorically more advanced than another. Rather, different parts of the consortium are positioned at different points in the transition from individual AI use to coherent educational and institutional maturity.

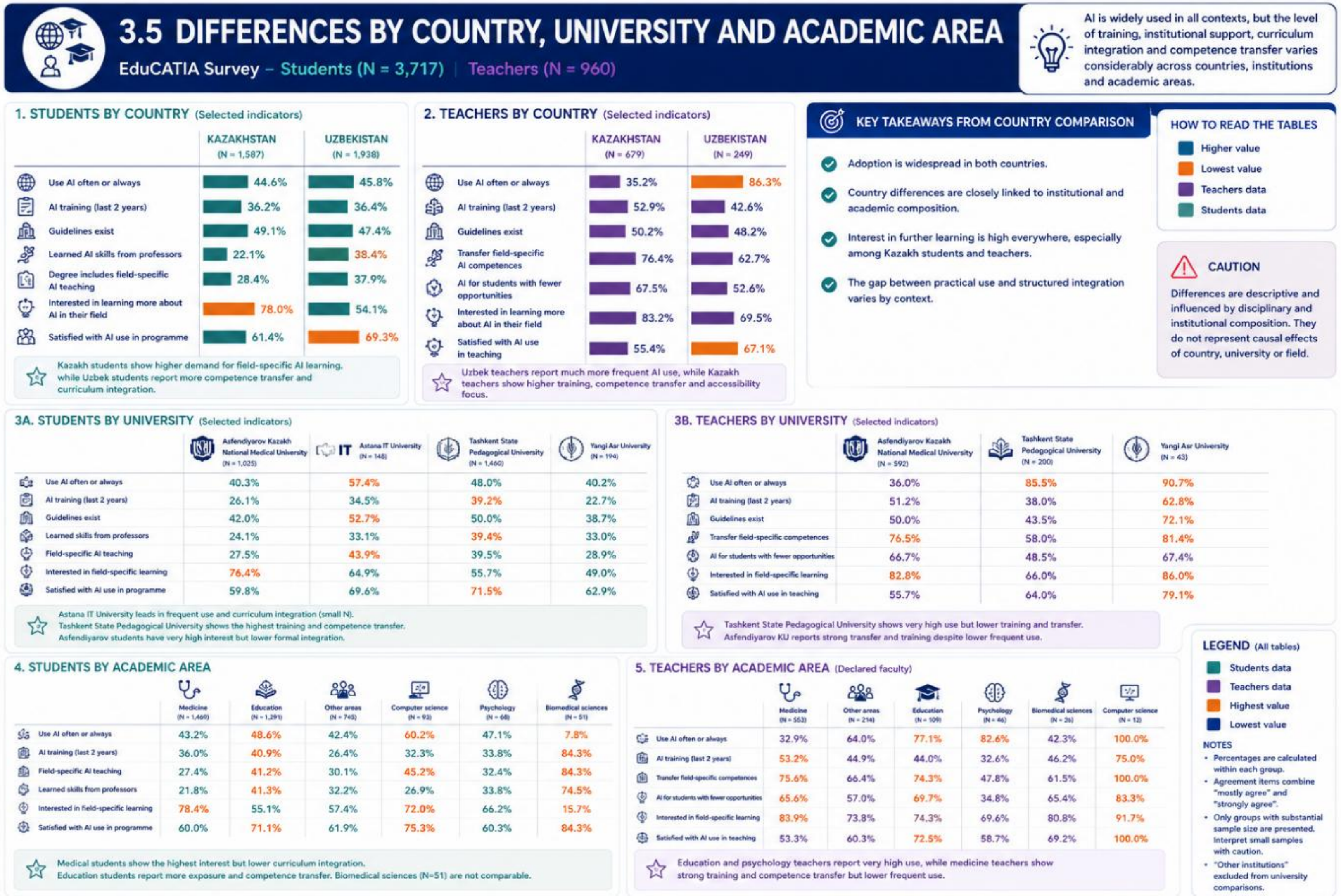

Figure 5. Differences by Country, University and Academic Area

Source: EduCATIA revised student and teacher datasets and disaggregated tables prepared by Simona Perone. Student questionnaire, valid N = 3,717; teacher questionnaire, valid N = 960.

Methodological note: Percentages are calculated within each country, university or academic group. Agreement indicators combine “mostly agree” and “strongly agree”. Institutional comparisons exclude aggregated “other institutions” and very small samples where appropriate. No weighting or inferential testing was applied.

3.6. Overall interpretation of the results

The combined analysis of the student and teacher questionnaires indicates that the institutions participating in EduCATIA are not at the initial stage of AI adoption. Artificial intelligence is already present in everyday study and teaching practices, and both groups use it for a broad range of academic purposes. The principal challenge is therefore no longer whether AI should enter higher education, but how its existing use can be transformed into explicit, critical, ethical and institutionally supported educational practice.

3.6.1. Adoption has advanced more rapidly than educational maturity

The strongest overall pattern is the gap between high practical use and more limited educational institutionalisation.

More than nine out of ten students and teachers use AI at least occasionally. However, only a small minority in either group describe their knowledge as advanced. Formal training, recognised institutional guidelines and field-specific curriculum integration reach substantially smaller proportions of respondents.

This suggests that AI adoption has developed largely through individual initiative, accessible general-purpose tools and informal experimentation. Use has expanded faster than the structures needed to guide it.

The findings therefore support a distinction between:

- access to AI tools;
- functional use of those tools;
- critical AI literacy;
- pedagogical and professional competence;
- institutional readiness and governance.

These stages should not be treated as interchangeable. Frequent use does not demonstrate that respondents can verify outputs, identify bias, protect sensitive data, document AI use or apply it responsibly in professional contexts.

3.6.2. The principal competence gap concerns the quality of use

The results do not indicate a general lack of familiarity with AI. Instead, they reveal uncertainty about the depth and quality of the competences being developed.

Students and teachers use AI for translation, data analysis, content production, accessibility and academic support. Teachers additionally use it to create assignments and teaching materials, while students frequently use it for tutoring and explanations.

However, the questionnaires do not show that these practices are consistently linked to explicit learning outcomes, structured feedback or assessment criteria. Nor do they demonstrate that users systematically evaluate the reliability and limitations of AI-generated outputs.

The central competence need is therefore not simply learning how to operate an AI tool. It is learning how to:

- select a suitable tool for a defined purpose;
- formulate and refine prompts or instructions;
- compare AI-generated and non-AI approaches;
- verify facts, evidence and references;
- detect hallucinations, bias and inappropriate generalisations;
- protect personal, institutional and sensitive data;
- explain and disclose how AI has been used;
- retain human responsibility for academic and professional decisions.

The survey findings suggest that these competences are not yet consistently visible as part of formal university learning.

3.6.3. Teachers are central to the transition from use to competence

Teachers report substantial use of AI and strong interest in further professional development. They also report transferring both general and discipline-specific AI competences to students.

Nevertheless, students are much less likely to state that they have learned AI skills from their professors. This discrepancy should not be interpreted as proof that teachers are not transferring competences. The two groups were not paired, and the relevant questions were not identical.

The contrast nevertheless reveals an important educational problem: AI-related teaching may remain implicit and therefore insufficiently recognisable to students.

Teachers may demonstrate tools, recommend applications or use AI in preparing materials without defining what students are expected to learn. In such cases, exposure to AI does not necessarily become an observable and assessable competence.

The results therefore point to the need to move from informal demonstration towards explicit competence design. Students should be able to recognise:

- which AI competence is being taught;
- why it is relevant to the discipline;
- what standards of quality and responsibility apply;
- how the competence will be practised;
- how its acquisition will be assessed.

Teacher development is consequently one of the main conditions for improving student AI competence.

3.6.4. Training is associated with more structured educational practice

The teacher analysis shows that respondents who had participated in university-organised training were more likely to use AI frequently, transfer competences, support accessibility and express satisfaction with their teaching practice.

These associations do not establish that training caused the differences. Teachers who are already interested in AI may be more likely to participate, and more supportive institutions may offer both training and clearer opportunities for integration.

Nevertheless, the consistency of the pattern provides a strong indication that training is linked to more mature forms of AI use.

The high level of interest among both trained and untrained teachers also shows that professional development should not be limited to a single introductory course. Training should be progressive and continuing, moving from basic literacy towards:

- pedagogical design;
- assessment and feedback;
- discipline-specific applications;
- ethics and data governance;
- accessibility and inclusion;
- evaluation of educational effectiveness;
- training-of-trainers capacity.

The results support the interpretation of teacher training as an institutional process rather than an isolated activity.

3.6.5. Institutional support remains uneven and insufficiently visible

Approximately half of both students and teachers report that institutional guidelines exist. This convergence suggests that the visibility of university-level AI governance is limited across both groups.

The inconsistencies found between questions on the existence and clarity of guidelines indicate that respondents may not share a common understanding of what counts as institutional guidance. They may refer to university policies, faculty-level instructions, recommendations from individual teachers or informal rules applied within particular courses.

The main issue is therefore not only whether a document exists. Effective institutional guidance must also be:

- visible;
- understandable;
- specific to university teaching and learning;
- applicable to different disciplines;
- connected to assessment practice;

- regularly updated;
- supported by examples and decision-making tools.

The findings suggest that formal policy and practical implementation are not yet fully aligned. Institutions may have some rules in place without those rules being sufficiently recognised or operationalised by the academic community.

3.6.6. Assessment is the most sensitive area of AI integration

Both groups show greater acceptance of AI when it is used to create or support content than when it is involved in assessment.

Students are particularly cautious about professors using AI to evaluate their competences. Teachers are more accepting of AI-assisted assessment, but they also express strong concern about dishonesty and the possible effects of AI on critical thinking.

This tension places assessment at the centre of the educational challenge.

Traditional take-home assignments, generic essays and tasks focused primarily on reproducing information may become less valid when AI can generate plausible outputs with limited student effort. A purely prohibitive response is unlikely to resolve this problem, particularly where students already use AI extensively.

The results imply that assessment must increasingly focus on processes that make learning visible. These may include documented workflows, critical comparison of sources, oral defence, reflective commentary, portfolios, supervised performance, iterative feedback and transparent disclosure of AI use.

The survey does not identify which assessment model is most effective, but it clearly shows that confidence in assessment is weaker than confidence in other AI-supported activities.

3.6.7. Perceived usefulness coexists with strong concern

Students generally report stronger direct learning benefits than teachers. They are more likely to state that AI helps them learn faster and better. Teachers are more cautious about these effects and considerably more concerned about students' critical thinking.

At the same time, both groups show only moderate agreement that AI improves the overall quality of teaching and learning.

This combination argues against both technological optimism and general rejection.

AI is perceived as useful, but its educational value cannot be assumed from use alone. The benefits depend on how activities are designed, which tools are selected, how outputs are checked and whether students remain intellectually engaged.

The difference in perspective between students and teachers is also important. Students experience immediate benefits such as speed, explanations, translation and personalised support. Teachers must additionally consider reliability, academic integrity, cognitive dependence and the validity of assessment.

These perspectives should be treated as complementary. Effective AI integration must preserve the practical advantages recognised by students while addressing the professional concerns expressed by teachers.

3.6.8. Critical thinking is the central transversal competence

Concern about critical thinking is one of the most important findings of the survey.

A substantial proportion of students believe that AI has reduced their own critical thinking, although most do not perceive this effect. Teachers are considerably more likely to believe that AI reduces students' critical thinking and to identify this as a major risk.

The survey cannot establish whether AI objectively weakens critical thinking. It measures perceptions rather than cognitive performance.

However, the contrast shows that critical thinking cannot be treated as an automatic outcome of higher education or as a competence separate from AI use. It must be deliberately integrated into AI-supported activities.

Students should not only obtain answers from AI. They should be required to:

- question those answers;
- identify unsupported claims;
- compare alternative explanations;
- examine sources and evidence;
- recognise uncertainty;
- justify whether an output should be accepted, revised or rejected;
- explain the limits of the tool used.

The central educational question is therefore not whether AI replaces thinking, but whether teaching designs AI use in a way that requires and strengthens thinking.

3.6.9. Disciplinary and institutional differences require differentiated responses

The analyses by country, university and academic area do not show a single linear progression from low to high AI maturity. Instead, they reveal different combinations of use, training, institutional support, curriculum integration and demand.

Some groups show high practical use but weaker formal structuring. Others report more training and competence transfer despite less frequent use. Medical students show particularly strong demand for field-specific AI learning, while reporting comparatively limited curriculum integration. Education students report more exposure through teachers and study programmes, although formal provision remains incomplete.

These patterns demonstrate that a uniform educational response would be inadequate.

Different fields require different combinations of general and professional competence:

- education requires attention to instructional design, assessment, learning analytics, accessibility and teacher responsibility;
- medicine requires reliability, explainability, patient safety, data quality and human oversight;
- biomedical sciences and public health require data analysis, epidemiological modelling, surveillance and health-data governance;

- psychological sciences require particular caution regarding privacy, bias, assessment, mental-health applications and professional supervision.

Institutional capacity-building should therefore begin from the profile of each university and academic area rather than from a standardised assumption that all partners face the same needs.

3.6.10. Inclusion and accessibility are established opportunities, not marginal concerns

AI-related accessibility use is already reported by substantial proportions of both students and teachers. Teachers also report using AI to support students with fewer opportunities.

This indicates that inclusion is not merely a future or theoretical application. It is already part of the practical AI environment of the participating institutions.

Potentially relevant applications include:

- translation and multilingual support;
- subtitles and speech-to-text tools;
- text-to-speech systems;
- simplified or alternative versions of learning materials;
- personalised explanations;
- support for students with sensory, linguistic or learning barriers.

However, reported use is not evidence that all applications are accessible, ethically appropriate or effective. Tools should be selected and evaluated with the participation of the students concerned, and they should not create new barriers through cost, language limitations, poor design or inappropriate data collection.

Accessibility should therefore be treated as a core quality criterion in AI integration, not as an optional additional feature.

3.6.11. Overall assessment of AI maturity

Taken together, the findings indicate that the participating institutions are located in an intermediate stage of AI development.

They have moved beyond initial awareness and isolated experimentation. AI is widely used, interest is high and several educational applications are already established.

However, the evidence does not yet indicate complete institutional maturity. The main limitations concern:

- low levels of advanced self-perceived knowledge;
- unequal access to formal training;
- incomplete curriculum integration;
- limited visibility of institutional guidelines;
- uneven transfer and recognition of competences;
- uncertainty surrounding assessment;
- strong concerns about reliability and academic integrity;

- insufficient evidence regarding educational effectiveness.

The most appropriate overall description is therefore **broad adoption with uneven educational and institutional maturity**.

This conclusion applies to the sample as a whole, but the disaggregated findings show that institutions and disciplines occupy different positions within this transition.

3.6.12. Final interpretative conclusion

The results demonstrate that the central task for EduCATIA is not to persuade students and teachers to begin using artificial intelligence. Use has already become widespread.

The project's added value lies instead in helping institutions transform dispersed and individual practices into:

- explicit student competences;
- professionally grounded teacher capacity;
- discipline-specific curricula;
- transparent assessment practices;
- accessible and inclusive learning opportunities;
- clear ethical and institutional governance.

The survey therefore supports a shift in emphasis from **AI adoption** to **AI educational maturity**.

AI should not be integrated merely as an additional tool for productivity. It should become the object of critical study, responsible professional application and pedagogically designed learning. Its contribution to higher education will depend less on the number of tools used than on the capacity of institutions, teachers and students to determine when, why and under what conditions those tools should be used.

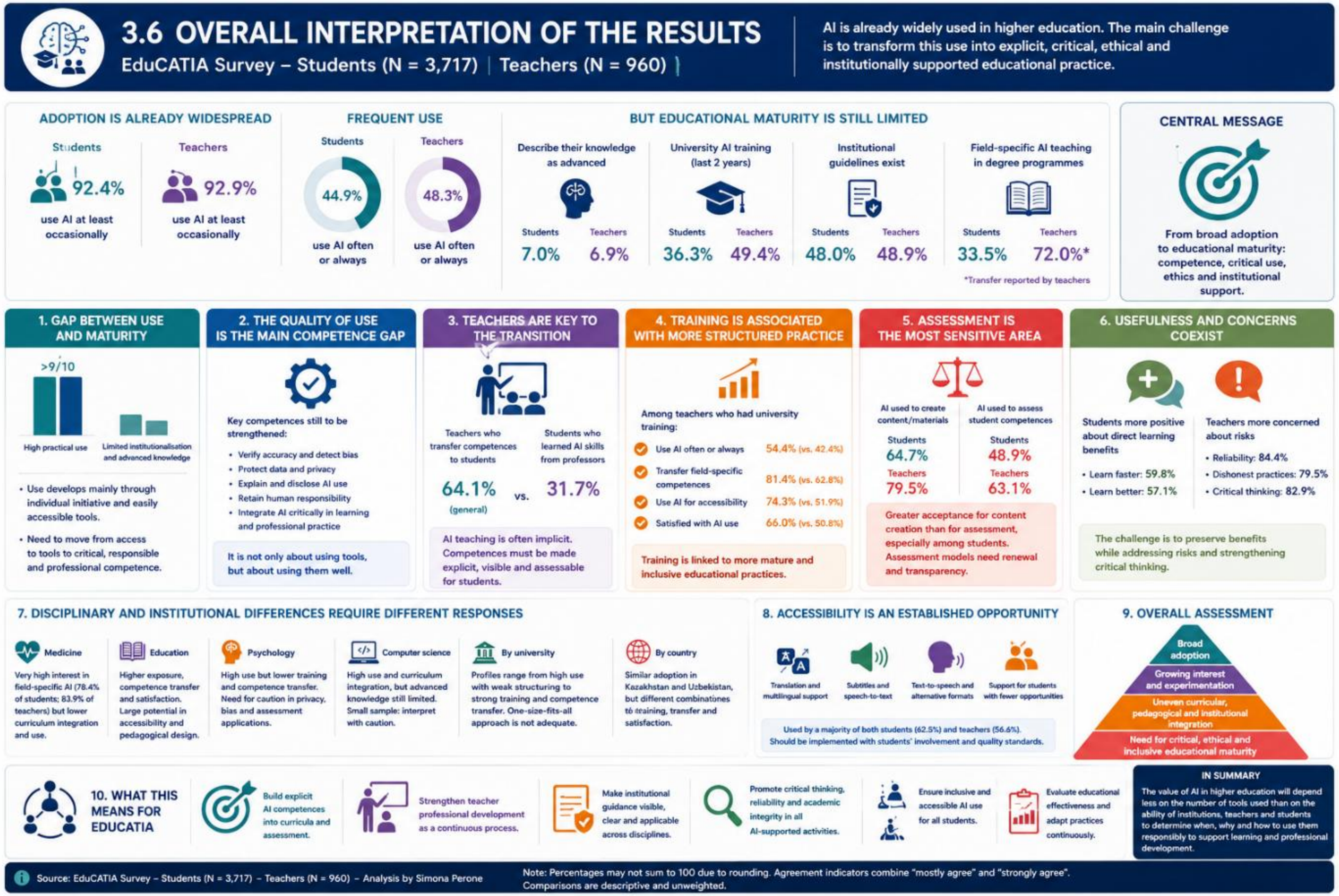

Figure 6. Overall Interpretation of the Results

Source: EduCATIA revised survey analysis and disaggregated tables prepared by Simona Perone. Student questionnaire, valid N = 3,717; teacher questionnaire, valid N = 960.

Methodological qualification: The interpretation is based on descriptive, self-reported and cross-sectional data. It identifies associations and patterns but does not establish causal relationships or statistically representative national estimates.

3.7. Impact of the research on the project

The questionnaire research performs a diagnostic, planning and monitoring function within EduCATIA. Its main contribution is to replace general assumptions about AI readiness with evidence concerning how students and teachers currently use AI, which competences they believe they possess, what support they receive and which educational and institutional needs remain insufficiently addressed.

The findings broadly confirm the relevance of the project's original objectives: curriculum modernisation, faculty capacity building, institutional policy reform, inclusive AI education and stronger university–industry cooperation. At the same time, they refine these objectives by showing that the principal challenge is no longer the initial introduction of AI tools. AI use is already widespread. The project must therefore focus on improving the **quality, visibility, responsibility and disciplinary relevance of that use**.

The research should consequently influence the design and implementation of the project in the following areas.

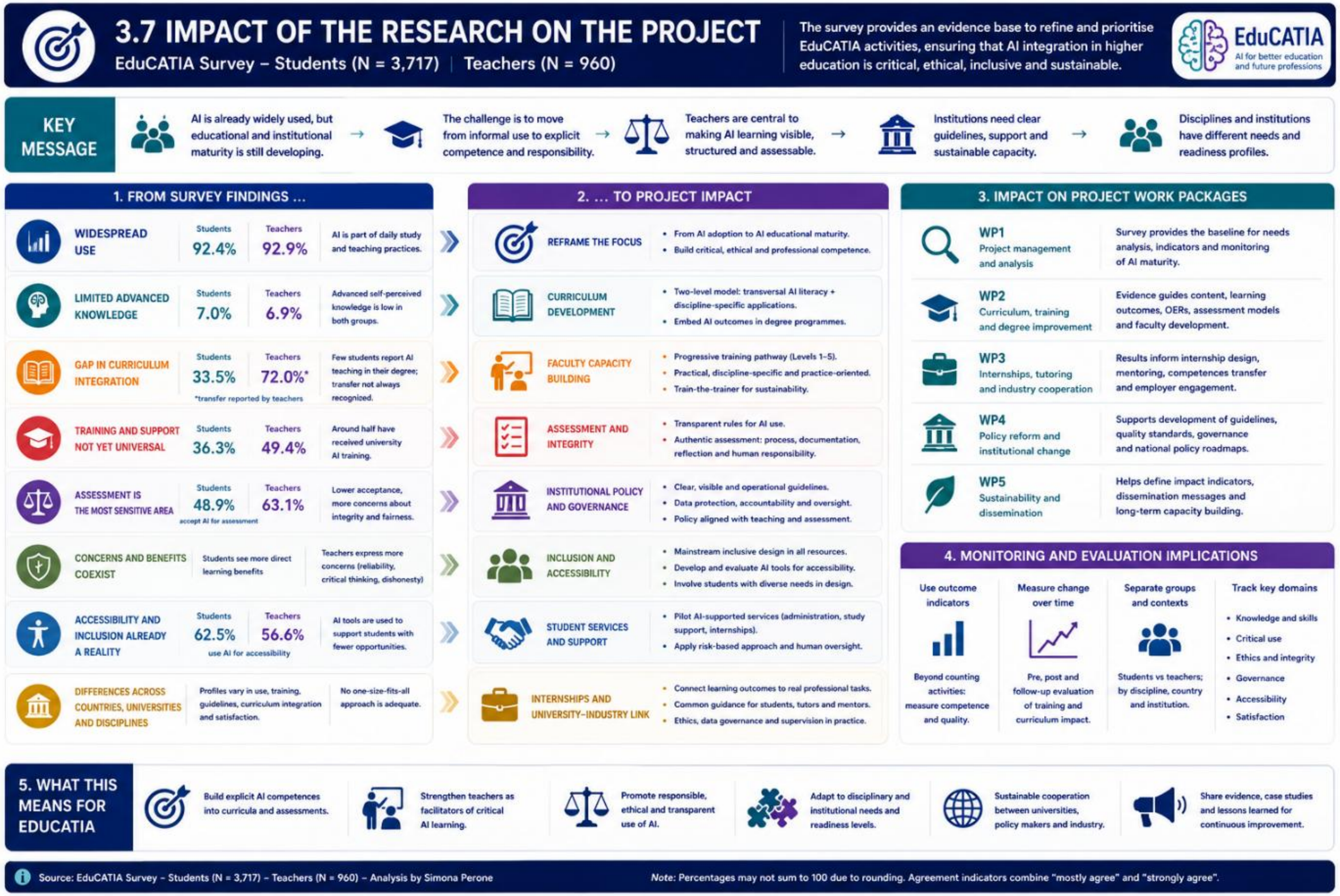

Figure 7. Impact of the Research on the Projec

3.7.1. Reorientation from AI adoption towards AI educational maturity

The survey demonstrates that more than nine out of ten students and teachers already use AI at least occasionally. Activities designed solely to raise awareness of the existence of AI would therefore respond only partially to the identified needs.

EduCATIA should use practical adoption as its starting point and focus on the transition from informal use to educational maturity. This means distinguishing between:

- access to AI tools;
- routine or functional use;
- critical AI literacy;
- pedagogical competence;
- discipline-specific professional competence;
- institutional governance and readiness.

This distinction should be reflected throughout the project. Training materials, curricula and policy documents should not treat the ability to use a general-purpose chatbot as equivalent to advanced AI competence.

The project should instead define maturity through observable capacities such as selecting an appropriate tool, evaluating outputs, identifying limitations, protecting data, documenting AI use, comparing alternative approaches and retaining human responsibility for decisions.

3.7.2. Impact on curriculum development and degree improvement

The findings provide a direct evidence base for the activities concerning degree improvement and the integration of AI into university curricula.

Only around one third of students report that their degree programme includes general or field-specific AI teaching. At the same time, almost two thirds want to learn more about AI in their field, with particularly strong demand among medical students.

This gap indicates that AI content should not be introduced solely through optional workshops or isolated technical subjects. It should be integrated into the intended learning outcomes of the programmes selected for modernisation.

A two-level curriculum model is recommended.

Common transversal component

All students, regardless of discipline, should develop a shared foundation that includes:

- understanding the basic capabilities and limitations of AI systems;
- selecting suitable tools for academic and professional tasks;
- formulating and refining prompts or instructions;
- verifying information and references;
- identifying hallucinations, bias and uncertainty;
- protecting personal and sensitive data;

- declaring and citing AI use;
- comparing AI-supported and non-AI approaches;
- understanding human responsibility and oversight;
- using AI in accordance with academic-integrity requirements.

Discipline-specific component

The common foundation should be complemented by learning outcomes adapted to each academic area.

In education and pedagogy, priority should be given to instructional design, adaptive learning, learning analytics, inclusive materials, feedback and assessment.

In medicine, emphasis should be placed on clinical decision support, medical imaging, data quality, explainability, patient safety, confidentiality and professional accountability.

In biomedical sciences and public health, relevant areas include data analysis, epidemiological modelling, disease surveillance, predictive analytics, resource planning and health-data governance.

In psychological sciences and cognitive research, particular attention should be given to behavioural analysis, psychological assessment, neuroimaging, affective computing, privacy, bias, mental-health applications and the limits of automated support.

The research therefore supports a curriculum model based neither on a single generic AI course nor on the unstructured introduction of tools into existing subjects. It supports a combination of transversal competence and situated professional application.

3.7.3. Formulation of observable learning outcomes

The gap between teachers' reported transfer of competences and students' recognition of having learned them has direct consequences for curriculum design.

EduCATIA should help partner institutions translate AI-related activities into observable learning outcomes. For example, students should be able to:

- justify the selection of an AI tool for a specific task;
- document the prompts, data and sources used;
- verify the accuracy of generated content;
- identify and correct errors or bias;
- explain which parts of a product were produced with AI;
- compare an AI-supported result with a non-AI alternative;
- assess the ethical and professional acceptability of an application;
- defend their final decisions independently of the AI system.

These outcomes should be communicated to students and aligned with teaching activities and assessment criteria. This would make competence transfer more visible and would allow the project to evaluate not only whether AI was used, but whether a recognisable competence was acquired.

3.7.4. Impact on faculty capacity building

Teacher training emerges as one of the areas in which the research should have the greatest impact.

Approximately half of the teachers have received university-organised AI training, while around four out of five express an interest in learning more. Teachers who have received training report more frequent use, stronger competence transfer, greater use of AI for accessibility and higher satisfaction with their teaching practice.

Although these relationships are not causal, they provide a strong empirical justification for prioritising faculty development.

Training should be structured as a progressive pathway rather than as a single introductory course.

Level 1. Foundational AI literacy

This level should cover basic concepts, available tools, common limitations, privacy, reliability and responsible use.

Level 2. Pedagogical integration

Teachers should learn how to design AI-supported activities, align them with learning outcomes, supervise student use and provide feedback.

Level 3. Assessment and academic integrity

Training should address authentic assessment, transparent rules, documentation of AI use, oral defence, portfolios, supervised tasks and criteria for distinguishing support from substitution.

Level 4. Discipline-specific application

Teachers should work with cases, data and professional scenarios from their own fields rather than relying exclusively on generic examples.

Level 5. Institutional leadership and training of trainers

Selected staff should be prepared to mentor colleagues, update resources, support policy implementation and sustain training after the end of the project.

The high level of interest among teachers who have already received training indicates that continuing professional development will be necessary. AI training should therefore be iterative, supported by communities of practice and connected to actual course redesign.

3.7.5. Impact on the design of open educational resources

The project foresees the development of open educational resources. The survey findings should determine both their content and format.

The resources should not consist only of theoretical introductions to AI. They should include:

- discipline-specific cases;
- sample teaching activities;
- assessment rubrics;
- examples of permitted and prohibited use;

- prompt and output documentation templates;
- verification checklists;
- data-protection scenarios;
- examples of hallucinations and bias;
- accessibility guidance;
- model declarations for acknowledging AI use;
- comparative activities using AI-supported and non-AI methods.

Resources should be modular so that institutions can combine a common AI-literacy component with materials specific to medicine, public health, education or psychology.

They should also be available in the languages most relevant to the partner institutions and designed according to accessibility principles. The strong use of AI for translation and accessibility makes multilingual and multi-format provision especially relevant.

3.7.6. Impact on assessment design and academic integrity

Assessment is the area in which the survey identifies the greatest ethical tension.

Both students and teachers are more accepting of AI for creating content than for evaluating competence. Teachers also express strong concern about dishonest practices and the possible reduction of critical thinking.

EduCATIA should therefore treat assessment redesign as a central project activity rather than as a secondary ethical topic.

Institutional and course-level assessment models should increasingly include:

- transparent statements about permitted AI use;
- documentation of prompts, outputs and revisions;
- explanation of the student's individual contribution;
- oral presentation or defence of submitted work;
- supervised practical activities;
- portfolios showing the development of a product;
- comparison and critique of AI-generated outputs;
- tasks based on local, professional or course-specific contexts;
- reflective accounts of errors, limitations and ethical decisions.

The purpose should not be to prohibit AI in every context or to assume that all AI use constitutes misconduct. It should be to ensure that assessment continues to provide valid evidence of student learning.

The project should also distinguish between low-risk uses, such as language support or brainstorming, and higher-risk uses that may obscure authorship, replace professional judgement or expose confidential data.

3.7.7. Impact on institutional policy and governance

Approximately half of both students and teachers recognise the existence of university AI guidelines. The inconsistencies in responses concerning their clarity suggest that existing guidance is not always visible, specific or operational.

The research should inform institutional-policy development by demonstrating that simply publishing a general policy document is insufficient.

Guidelines should answer concrete questions:

- Which AI uses are permitted in teaching and student work?
- Which uses require prior authorisation?
- When must AI use be declared?
- How should it be cited or documented?
- Which data must never be entered into external systems?
- Who remains responsible for AI-supported decisions?
- Under what conditions may AI be used in assessment?
- Which tools are institutionally recommended or supported?
- How can students contest an AI-supported evaluation?
- What safeguards apply in medicine, psychology and other sensitive fields?

Guidance should be concise enough for routine use but supported by more detailed disciplinary protocols and examples.

The questionnaire results should also be used in the policy-review and capacity-building activities foreseen under the project's policy-reform work. They provide evidence of policy–practice gaps and can support the preparation of institutional, national and regional recommendations. The project application explicitly links policy analysis, stakeholder participation and national frameworks to the modernisation of AI education in Kazakhstan and Uzbekistan.

3.7.8. Impact on inclusion and accessibility

The survey identifies accessibility as an established area of AI use. More than half of both students and teachers use AI for accessibility-related purposes, and a substantial proportion of teachers use it to support students with fewer opportunities.

This finding should influence the project in three ways.

First, accessibility should be incorporated into the core curriculum and teacher-training programme rather than treated as an optional specialist topic.

Second, all platforms, laboratories and open resources developed by the project should be reviewed for accessibility and multilingual usability.

Third, students with disabilities, learnThird, where relevant to the scope of the pilot, universities should include representatives of the intended student groups in accessible and ethically appropriate consultation and testing activities. Their feedback should be used to assess usability, accessibility, linguistic clarity and potential unintended barriers before wider implementation. ing difficulties, linguistic barriers and fewer opportunities should be involved in the design and evaluation of relevant pilots.

Potential applications include:

- subtitles and automatic transcription;
- text-to-speech and speech-to-text systems;
- translation and multilingual support;
- simplified or alternative versions of materials;
- personalised explanations;
- support for planning and organisation;
- accessible interfaces and alternative formats.

The project should not assume that an AI tool is inclusive merely because it offers an accessibility function. Tools should be evaluated for accuracy, affordability, data protection and the risk of creating new forms of exclusion.

3.7.9. Impact on AI-supported student services

More than half of the students express interest in AI-supported administrative tutoring, internship support, AI-generated lessons and initial psychological support.

These findings justify pilot initiatives, but they also indicate the need to distinguish between services with different risk levels.

Lower-risk pilots

Appropriate initial pilots may include:

- administrative information assistants;
- study-orientation tools;
- internship information and planning support;
- multilingual access to university procedures;
- academic-writing and study-resource support.

Higher-risk pilots

Applications involving psychological support, student assessment, sensitive health data or professional decision-making require stronger safeguards.

Such services should include:

- clearly defined limits;
- immediate access to human professionals;
- protection of sensitive information;
- emergency and escalation procedures;
- transparent communication that the system is not a professional substitute;
- continuous monitoring of errors, bias and inappropriate advice.

Student interest should therefore be interpreted as support for controlled experimentation, not as evidence that universities should automate these services without supervision.

3.7.10. Impact on internships, tutoring and university–industry cooperation

The survey results have direct implications for the activities concerning transitions to employment, internships and mentoring.

Students show interest in AI-supported tutoring during internships, while the wider analysis demonstrates a demand for discipline-specific and professionally applicable competence.

Internship models should therefore enable students to apply AI in authentic professional settings while documenting:

- the problem addressed;
- the tool and data used;
- professional and ethical constraints;
- output-verification procedures;
- the role of human supervision;
- the limitations identified;
- the competence acquired.

Industry and hosting organisations should participate not only by offering placements, but also by helping universities identify relevant professional tasks, data-governance requirements and emerging competence needs.

University tutors and workplace mentors should receive common guidance so that AI-supported activities are assessed consistently. Particular care will be necessary in health, psychological and educational settings, where students may encounter personal or sensitive data.

The research thus supports the project's intention to connect curriculum development with internships, mentoring and employer cooperation. The project application positions these activities within WP3 and links them to practical competence, job readiness and university–industry partnerships.

The preceding findings have implications that extend beyond the interpretation of individual questionnaire items. Taken together, they provide an initial evidence base for curriculum modernisation, faculty development, institutional guidance and the design of subsequent EduCATIA activities. The following section clarifies the scope of this contribution and the additional evidence required before programme-level changes can be specified.

3.7.11. Implications of the findings for curriculum modernisation and subsequent EduCATIA activities

The preceding findings have implications that extend beyond the interpretation of individual questionnaire items. Taken together, they provide an initial evidence base for curriculum modernisation, faculty development, institutional guidance and the design of subsequent EduCATIA activities. Their principal contribution is to identify the competences, institutional conditions and disciplinary priorities that should guide the next stages of the project.

At the same time, the questionnaire study does not constitute a complete curriculum-review exercise. The instruments were designed as a cross-disciplinary needs assessment covering AI use, training, competence transfer, curriculum visibility, ethical acceptance, institutional support and perceived professional relevance. They were not based on a line-by-line examination of the degree programmes selected for modernisation.

The present analysis can therefore identify common priorities, competence gaps and curriculum-design principles, but it cannot yet determine the precise subjects, credit allocations, module sequences or institutional procedures through which each programme should be modified.

Scope of the questionnaire evidence

The academic-area analysis provides a preliminary orientation for curriculum development across education and pedagogy, medicine, biomedical sciences and public health, and psychological sciences and cognitive research. It identifies both shared needs and discipline-related differences in practical AI use, training, competence transfer, ethical concerns, risk perception and institutional support.

These broad academic categories should not, however, be treated as substitutes for the actual structure of the programmes selected for renewal. Programmes situated within the same general area may differ substantially in their learning outcomes, professional profiles, accreditation requirements, existing digital content, assessment methods and current level of AI integration.

The survey findings consequently do not establish which existing modules should be retained, revised, combined or supplemented. Nor do they support the automatic introduction of a uniform AI subject into every programme. Curriculum decisions should instead be based on the specific educational and professional functions that AI may perform within each degree.

Priorities emerging from the findings

The evidence indicates that curriculum modernisation should not be limited to introducing students and teachers to individual AI tools. It should distinguish among:

- functional tool use;
- critical AI literacy;
- disciplinary and professional competence;
- pedagogical integration;
- ethical and institutional governance.

Across programmes, students should progressively develop the capacity to:

- select AI tools that are appropriate to a clearly defined academic or professional task;
- formulate and refine prompts or instructions;
- verify outputs against reliable evidence and disciplinary knowledge;
- identify factual errors, hallucinations, bias and unsupported claims;
- compare AI-supported and non-AI approaches;
- document and declare relevant AI use;

- protect personal, confidential and sensitive data;
- recognise situations in which AI should not be used;
- retain human responsibility for academic and professional decisions.

These competences should be translated into observable learning outcomes and assessed through tasks that require explanation, verification, judgement and reflection, rather than only the production of an AI-assisted output.

Next stage of programme-level curriculum review

The next stage should examine the actual educational provision of each degree programme selected for modernisation. Where available, the review should consider:

- intended programme and module learning outcomes;
- the structure and sequence of modules;
- existing AI-, digital- and data-related content;
- teaching and learning activities;
- assessment methods;
- internship, tutoring and professional-practice components;
- ethical, legal and data-governance requirements;
- accessibility and inclusion provisions;
- relevant accreditation and professional standards;
- available institutional infrastructure and staff capacity.

This review should identify where AI-related competences are already present, where they remain implicit and where genuinely new content or learning activities are required. It should also distinguish between competences that need to be developed across the whole programme and those that belong in specific disciplinary modules.

For example, verification, transparency, responsible use and data protection may require programme-wide treatment, whereas clinical decision support, epidemiological modelling, learning analytics or behavioural assessment should be addressed within the relevant professional and disciplinary contexts.

Triangulation of evidence

Programme-level recommendations should be developed through the combined use of three sources of evidence:

1. the questionnaire findings;
2. the focus-group evidence;
3. the structured review of the curricula selected for modernisation.

The questionnaires provide information about reported practices, perceptions, training and institutional support. The focus groups can clarify how these patterns operate in actual teaching and learning environments, including barriers that may not be visible in closed-response data. The curriculum review can establish what is currently taught, how competence is assessed and where realistic changes can be introduced.

Triangulation is particularly important because self-reported use does not constitute an objective measurement of competence, and broad disciplinary categories do not reveal the detailed content of individual programmes. Recommendations should therefore be adopted only after checking that they are supported by the relevant combination of survey evidence, stakeholder experience and curriculum documentation.

Implications for faculty development

Curriculum change will depend on corresponding teacher capacity. The findings show that the practical use of AI has developed more rapidly than advanced knowledge, explicit competence transfer and institutional guidance. Faculty development should consequently be aligned with the intended curriculum changes rather than organised as a separate or generic activity.

Training should help teachers to:

- design learning activities in which AI supports rather than replaces student reasoning;
- formulate observable AI-related learning outcomes;
- integrate verification, bias detection and source evaluation into teaching;
- redesign assessment for contexts in which students may use generative AI;
- provide transparent guidance on permitted and non-permitted uses;
- evaluate AI-assisted work without relying exclusively on automated detection;
- protect personal and disciplinary data;
- use AI to improve accessibility and multilingual provision;
- adapt applications to their own academic field;
- explain the limits of AI-supported professional decisions.

A differentiated training architecture is therefore preferable to a single introductory course. It should include foundational AI literacy, pedagogical integration, assessment and academic integrity, discipline-specific applications, accessibility and inclusion, and training-of-trainers activities.

Implications for assessment

Assessment should be treated as a central component of curriculum modernisation. The questionnaire results show lower acceptance and greater uncertainty when AI is used in assessment than when it is used to create or support teaching materials.

Each programme should therefore review:

- which forms of AI use are permitted in assessed work;
- how students should declare or document that use;
- which stages of a task must remain demonstrably the student's own;
- how the reasoning process can be made visible;
- how oral defence, supervised work, portfolios or staged submissions may complement take-home assignments;
- how AI-assisted and non-AI approaches can be compared;

- how disciplinary judgement and professional responsibility are assessed.

The purpose should not be to prohibit AI generically or to assume that every use is acceptable. It should be to design assessment in which students must demonstrate understanding, verification, decision-making and responsibility.

Implications for institutional governance

Curriculum integration also requires clear and operational institutional conditions. Universities should provide guidance covering permitted use, disclosure, citation, data protection, procurement, accessibility, assessment and human oversight.

Such guidance should be sufficiently specific to support day-to-day decisions but flexible enough to accommodate disciplinary differences and technological change. Responsibility should be distributed clearly among programme leaders, teaching staff, ethics and data-protection structures, student-support services and technical units.

Where universities pilot AI-supported services or learning environments, these initiatives should include:

- a defined educational or administrative purpose;
- an assessment of risks and data requirements;
- clear human responsibility;
- accessibility and inclusion review;
- transparent information for users;
- criteria for monitoring effectiveness and unintended consequences;
- a procedure for revision or withdrawal.

Relevant pilots should include an accessibility and inclusion review. Where feasible and ethically appropriate, this review should incorporate feedback from students who may face disability-related, learning, linguistic or socioeconomic barriers. Participation should be voluntary, appropriately supported and designed so that feedback can influence the final configuration of the service.

Implications for discipline-specific curriculum development

The shared competence framework should be complemented by field-specific pathways.

In education and pedagogy, curriculum development should address adaptive learning, learning analytics, instructional design, authentic assessment, teacher AI literacy, metacognition, inclusion and governance.

In medicine, emphasis should be placed on clinical decision support, diagnostic applications, medical imaging, personalised medicine, telemedicine, explainability, data quality, patient safety, confidentiality and human oversight.

In biomedical sciences and public health, priorities should include biomedical data analysis, epidemiological modelling, disease surveillance, predictive analytics, health-resource planning, reproducibility, population bias and health-data governance.

In psychological sciences and cognitive research, the curriculum should address behavioural analysis, psychological assessment, cognitive modelling, neuroimaging, affective computing, mental-health applications, privacy, bias, professional supervision and the limits of automated support.

These pathways should not be treated as fixed lists of topics. Their inclusion and depth should be determined through the review of the relevant programmes, professional requirements and available institutional capacity.

Connection with subsequent EduCATIA activities

The survey findings should inform several interconnected project activities:

- the analysis and redesign of the selected degree programmes;
- the development of AI-related educational modules and learning outcomes;
- faculty capacity building and training-of-trainers activities;
- the modernisation of internship and tutoring practices;
- the testing of AI-supported educational and professional models;
- the preparation of institutional and policy guidance;
- the development of accessible educational resources;
- cooperation with professional organisations and relevant economic sectors.

The findings should not be interpreted as prescribing identical solutions across all institutions. The comparative analysis shows that participating universities and academic areas occupy different positions in the transition from individual AI use to coherent educational and institutional maturity. Some contexts primarily require formal guidance and foundational competence development; others require more advanced disciplinary applications, assessment redesign or mechanisms for making competence transfer explicit and recognisable to students.

The appropriate project response is therefore a differentiated model based on shared principles but adapted to programme-level needs, institutional readiness and professional context.

Expected contribution to curriculum modernisation

The contribution of the questionnaire study is diagnostic and strategic rather than prescriptive. It identifies where modernisation is most needed, which competences should receive priority and which institutional conditions must accompany curriculum change.

Its findings should be used to ensure that the renewed programmes do not merely increase exposure to AI tools, but develop students' capacity to use AI critically, transparently, safely and professionally. Curriculum modernisation should also strengthen teachers' ability to design, supervise and assess AI-supported learning and should provide institutions with clearer frameworks for responsible implementation.

The expected result is therefore not the uniform insertion of AI into every subject. It is the development of coherent learning pathways in which AI competence is connected to disciplinary knowledge, professional judgement, ethical responsibility, inclusion and institutional governance.

3.7.12. Differentiated implementation across institutions and disciplines

The disaggregated results show that partner institutions do not share a single profile of AI readiness.

Some institutions display high practical use but more limited formal training and guidance. Others report stronger training or competence transfer despite less frequent use. Medical students show particularly high demand for field-specific learning, whereas education students report greater exposure through teachers and curricula.

EduCATIA should therefore avoid a uniform implementation model.

Each participating institution should prepare a concise AI-needs profile based on:

- current levels of use;
- training already available;
- visibility of guidelines;
- curriculum integration;
- disciplinary priorities;
- staff capacity;
- infrastructure;
- accessibility needs;
- relations with professional and industry partners.

On this basis, project activities can combine common quality standards with different institutional priorities.

For example:

- one institution may need an introductory train-the-trainer programme;
- another may need advanced assessment redesign;
- another may require discipline-specific clinical or public-health modules;
- another may need support in converting high informal adoption into formal curriculum provision;
- another may need governance, data-protection and tool-validation procedures.

This differentiated approach is more consistent with the evidence than applying the same sequence of activities to every partner.

3.7.13. Impact on monitoring and evaluation

The questionnaires provide a baseline for monitoring the development of AI maturity during the project.

However, project monitoring should not rely only on activity counts such as the number of people trained, modules created or events organised. These indicators measure implementation but not necessarily educational change.

The baseline survey suggests the inclusion of outcome indicators concerning:

- changes in self-perceived knowledge;
- ability to verify AI-generated information;

- awareness of bias and hallucinations;
- knowledge of data-protection requirements;
- confidence in designing AI-supported activities;
- student recognition of AI competence acquired from teachers;
- integration of observable AI learning outcomes into courses;
- clarity and awareness of institutional guidelines;
- quality of AI-supported assessment;
- accessibility of resources and services;
- satisfaction with training and curriculum integration;
- continuation of practices after the end of training.

Where methodologically possible, pre-training and post-training measurements should be used. Follow-up measurement should also be considered, since immediate satisfaction does not demonstrate sustained change.

The project's evaluation should retain separate indicators for students and teachers and should distinguish general AI literacy from discipline-specific competence.

The project application already foresees monitoring of curricula, faculty development, student engagement, inclusion, industry collaboration and sustainability. The questionnaire results allow these indicators to be refined by adding measures of competence quality and institutional maturity.

3.7.14. Impact on dissemination and sustainability

The findings should also guide project dissemination.

Communication should avoid presenting AI exclusively as an innovation to be adopted. It should communicate a balanced message:

- AI is already widely used;
- its benefits are recognised;
- advanced competence remains limited;
- reliability, ethics and critical thinking require attention;
- institutions need clear and applicable frameworks;
- disciplines require different forms of integration.

The project should disseminate not only final curricula and training resources, but also:

- practical case studies;
- evidence from pilot activities;
- assessment models;
- institutional-policy templates;
- accessibility checklists;
- lessons learned from unsuccessful or problematic uses;

- indicators for monitoring AI maturity.

Sustainability will depend on whether the project creates local capacity to update these resources after technologies change. Train-the-trainer arrangements, institutional working groups, permanent learning hubs and continued university–industry cooperation are therefore more important than reliance on a fixed set of tools.

The survey can also provide the initial reference point for later impact evaluation. Repeating selected core questions would allow the project to examine whether training, curriculum reform and policy development have increased competence and institutional support.

3.7.15. Consolidated relationship between findings and project activities

Main survey finding	Consequence for EduCATIA	Main project area
AI use is already widespread	Move from awareness-raising to critical and professional competence	WP2, WP4
Advanced knowledge is uncommon	Develop progressive and continuing training pathways	WP2
Student curriculum integration is limited	Embed explicit general and field-specific learning outcomes	WP2
Teachers report greater transfer than students recognise	Make competences visible, practised and assessable	WP2
Teachers show strong demand for training	Prioritise practical, discipline-specific and train-the-trainer models	WP2
Assessment has the lowest acceptance	Redesign assessment and establish transparent AI-use rules	WP2, WP4
Reliability and critical thinking are major concerns	Integrate verification, bias detection and critical analysis into all modules	WP2, WP4
Guidelines reach only around half of respondents	Develop visible, operational and discipline-sensitive governance	WP4
Accessibility use is already substantial	Mainstream inclusive design and evaluate accessibility pilots	WP2, WP3, WP4
Students express interest in AI-supported services	Pilot services according to risk, with human oversight	WP2, WP3
Institutions and disciplines have different profiles	Adapt implementation plans to local and disciplinary needs	WP1, WP2, WP4

Students want professionally relevant competence	Connect curriculum outcomes to internships and industry tasks	WP3
The survey provides a baseline	Add outcome and maturity indicators to project evaluation	WP1, WP5
Long-term maturity requires local capacity	Maintain training networks, OERs, policies and partnerships	WP5

4. Conclusions

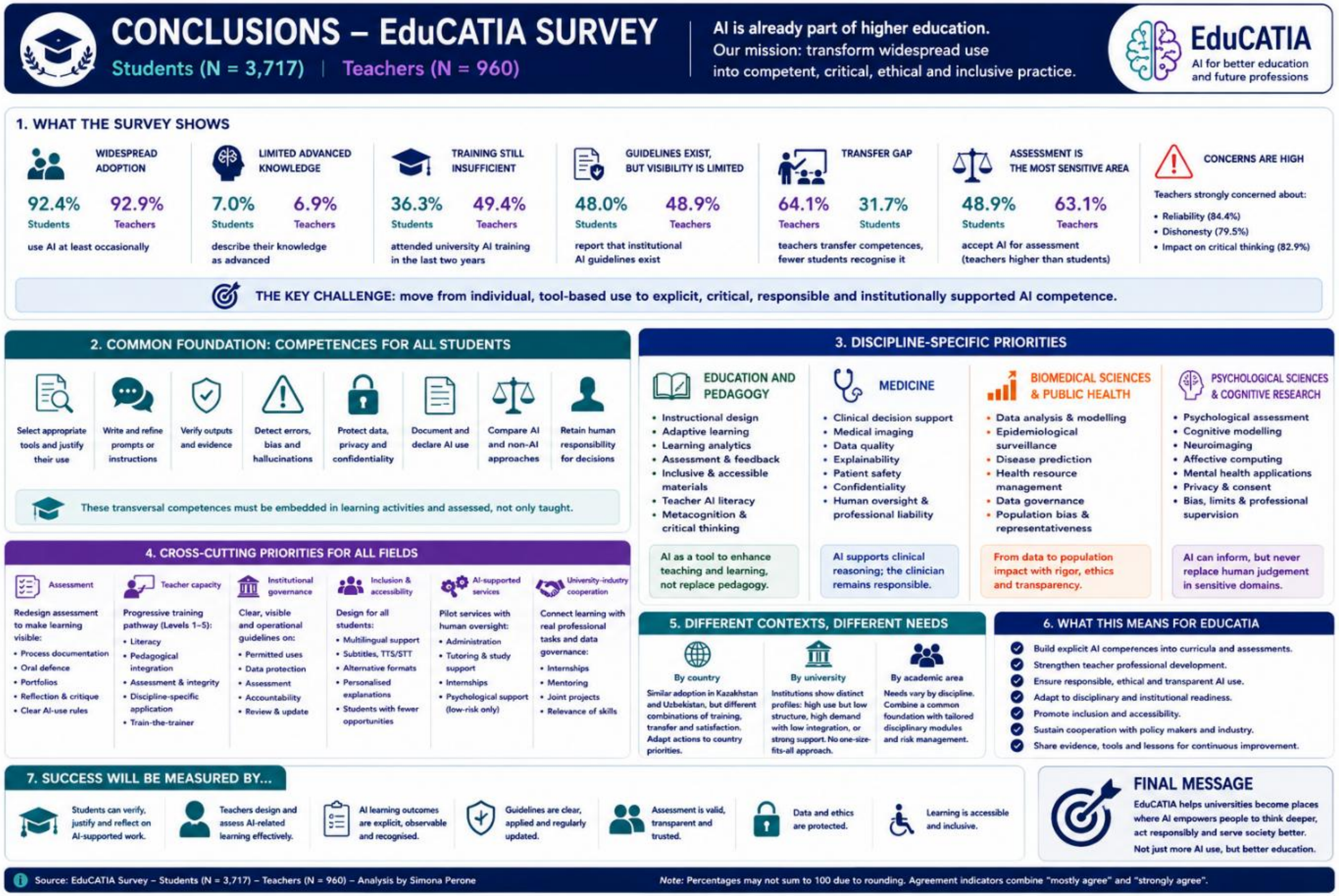

Figure 8. Conclusion - EduCATIA Survey

4.1. Common pedagogical foundation across academic areas

Although each academic field requires distinct applications and safeguards, the survey supports the creation of a common foundation of AI competence for all EduCATIA programmes.

This common component should not be limited to explanations of how AI systems function. It should enable students to demonstrate that they can:

1. identify when AI is appropriate for an academic or professional task;
2. select a suitable tool and explain the reasons for that selection;
3. formulate, test and refine prompts or instructions;
4. verify outputs against reliable evidence and disciplinary knowledge;
5. detect hallucinations, bias, omissions and inappropriate generalisations;
6. distinguish plausible language from valid evidence;
7. protect personal, institutional and sensitive data;
8. document and disclose how AI has been used;
9. compare AI-supported and non-AI approaches;
10. retain responsibility for the final interpretation and decision.

These competences should be incorporated into learning activities and assessment rather than presented only as theoretical guidance.

The common component should then be complemented by discipline-specific modules. The project application itself recognises that AI applications, risks and professional responsibilities differ across medicine, public health, education and psychological sciences.

4.2. Education and pedagogy

Finding

Students and teachers in education report relatively extensive exposure to AI. Compared with medicine, education students are more likely to report training, competence acquisition through professors and field-specific curriculum integration. Education teachers also report frequent use, substantial transfer of competences, accessibility-related applications and comparatively high satisfaction.

Evidence

Among education students:

- 48.6% use AI often or always;
- 40.9% have participated in university AI training;
- 41.3% report learning AI skills from professors;
- 41.2% report field-specific AI teaching in their programme;
- 55.1% want to learn more about AI within their field;
- 71.1% are satisfied with AI use in their programme.

Among education teachers:

- 77.1% use AI often or always;
- 44.0% have received university AI training;
- 74.3% report transferring field-specific AI competences;
- 69.7% use AI to support students with fewer opportunities;
- 74.3% want to acquire further field-specific competence;
- 72.5% are satisfied with their use of AI.

Interpretation

Education displays a profile of relatively high adoption and comparatively visible competence transfer. This is consistent with the immediate applicability of AI to lesson preparation, material adaptation, tutoring, accessibility, feedback and assessment.

However, fewer than half of education students report formal training or field-specific AI teaching. High use should therefore not be confused with complete curriculum integration.

Furthermore, education teachers must prepare not only current university students but also future teachers and educational professionals. Weaknesses in teacher AI literacy may consequently be transferred to subsequent generations of learners.

Pedagogical implication

In education and pedagogy, AI should be treated as both:

- a tool that can support teaching and learning;
- an object of critical pedagogical study.

Students should learn not only how to generate materials or activities, but how AI changes instructional design, teacher responsibility, student autonomy and the interpretation of learning evidence.

Recommended action

EduCATIA should develop an education and pedagogy pathway covering:

- AI-supported instructional design;
- adaptive and personalised learning;
- learning analytics;
- automated and AI-supported feedback;
- authentic assessment and academic integrity;
- inclusive and accessible material design;
- multilingual learning support;
- teacher–student interaction in AI-supported environments;
- bias and fairness in educational systems;
- governance of student data;
- metacognition and critical thinking;

- evaluation of whether an AI-supported activity improves learning.

Teachers should be trained to design activities in which students use AI to compare, justify, revise, challenge and reflect, rather than merely to generate final answers.

Suitable assessment methods include reflective portfolios, documented prompt and revision processes, oral defence, comparison of AI-generated alternatives and evaluation of the quality of evidence used.

4.3. Medicine

Finding

Medicine presents one of the clearest gaps between demand for AI competence and recognised curriculum provision.

Medical students show very high interest in field-specific AI learning, but comparatively few report learning AI skills from professors or encountering field-specific AI teaching in their degree. Medical teachers report strong interest and substantial competence transfer, despite comparatively less frequent use.

Evidence

Among medical students:

- 43.2% use AI often or always;
- 36.0% have received university AI training;
- 21.8% report learning AI skills from professors;
- 27.4% report field-specific AI teaching;
- 78.4% want to learn more about AI in medicine;
- 60.0% are satisfied with AI use in their programme.

Among medical teachers:

- 32.9% use AI often or always;
- 53.2% have participated in university training;
- 75.6% report transferring field-specific competence;
- 65.6% use AI to support students with fewer opportunities;
- 83.9% want to acquire further field-specific competence;
- 53.3% are satisfied with their use of AI.

Interpretation

The medical results indicate strong awareness of AI's professional relevance, combined with relatively limited formal curriculum integration from the student perspective.

The difference between teacher-reported competence transfer and student-recognised learning is especially important. Medical teachers may discuss or demonstrate AI applications without converting them into explicit and assessable learning outcomes.

Lower frequency of use among teachers should not automatically be interpreted as resistance. Medical applications involve high standards of reliability, patient safety, confidentiality, explainability and professional accountability. A more selective approach may therefore be appropriate.

Pedagogical implication

Medical AI education must go beyond general-purpose generative tools. It should prepare students to evaluate AI-supported clinical information without delegating professional judgement.

The educational emphasis should be on the relationship between technological output and clinical reasoning.

Students should be able to:

- evaluate the quality and provenance of clinical data;
- distinguish decision support from autonomous decision-making;
- assess sensitivity, specificity, uncertainty and potential error;
- explain the limits of a model to patients and colleagues;
- recognise bias affecting different patient groups;
- protect patient confidentiality;
- identify when an AI recommendation should be rejected;
- retain responsibility for clinical decisions.

Recommended action

The medical pathway should include:

- AI-assisted diagnostics;
- medical imaging and pathology applications;
- clinical decision-support systems;
- personalised medicine and predictive models;
- telemedicine and remote monitoring;
- medical robotics where relevant;
- data quality and representativeness;
- explainability and uncertainty;
- patient safety;
- confidentiality and health-data governance;
- professional liability and human oversight.

Teaching should use supervised case-based learning, simulations and comparison between clinician-only and AI-supported decisions.

Assessment should require students to interpret outputs, detect unsafe recommendations, justify clinical decisions and communicate uncertainty. It should not assess competence merely through the ability to operate a tool.

Co-funded by the European Union

The strong unmet demand among medical students makes medicine a priority area for explicit field-specific curriculum integration.

4.4. Biomedical sciences and public health

Finding

The quantitative evidence for biomedical sciences is limited by small subgroup sizes and an unusual response profile. Public health was not isolated as a directly equivalent closed category in the final questionnaire structure.

The survey therefore does not support robust generalisations about the entire biomedical sciences and public-health population.

Evidence

The biomedical sciences subgroup contains only 51 students and 26 teachers. Several percentages differ sharply from the patterns observed in other disciplines, suggesting possible institutional concentration, classification effects or distinctive local circumstances.

Public-health respondents may be distributed across medicine, biomedical sciences and other categories. Their results cannot be separated reliably using the current closed faculty variable.

Interpretation

The small and potentially heterogeneous sample means that pedagogical conclusions for this area should be based on:

- cautious interpretation of the questionnaire;
- the overall cross-disciplinary findings;
- the programmes selected for modernisation;
- the project's disciplinary framework;
- subsequent curriculum review and stakeholder consultation.

The findings should not be used to claim that biomedical-sciences students have either exceptionally high or low AI maturity without further verification.

Pedagogical implication

Biomedical sciences and public health require AI competence focused on data, population-level reasoning, reproducibility and governance.

Unlike individual clinical decision-making, public-health applications often operate at the level of populations, systems and resource allocation. Errors may affect entire communities or produce unequal outcomes across social groups.

Students therefore need to understand not only predictive performance, but also data representativeness, epidemiological interpretation and the consequences of algorithmic decisions for different populations.

Recommended action

The biomedical sciences and public-health pathway should include:

- biomedical data analysis;
- bioinformatics and laboratory-data interpretation;

- epidemiological modelling;
- outbreak detection and disease surveillance;
- predictive analytics;
- vaccination and prevention strategies;
- health-resource planning;
- digital-health literacy;
- population bias and data representativeness;
- reproducibility and validation;
- privacy and health-data governance;
- communication of uncertainty to policymakers and the public.

Learning activities should use anonymised or synthetic datasets and require students to document analytical decisions, evaluate data limitations and compare AI-generated conclusions with established epidemiological or biomedical methods.

Students should be able to explain why a statistically strong model may still be inappropriate for a particular population or policy decision.

Before finalising the renewed curricula, the project should undertake a targeted review of the biomedical and public-health programmes because the current survey subgroup is insufficient for detailed needs assessment.

The project framework identifies epidemiological research, disease surveillance, healthcare management and patient-centred digital-health solutions as key professional applications for this area.

4.5. Psychological sciences and cognitive research

Finding

The psychological-sciences subgroup shows high teacher adoption but more limited formal training, competence transfer and accessibility-related use. Students express interest in further learning, but only a minority report field-specific curriculum integration.

Evidence

Among psychology students:

- 47.1% use AI often or always;
- 33.8% have received university training;
- 33.8% report learning AI skills from professors;
- 32.4% report field-specific AI teaching;
- 66.2% want to acquire further field-specific competence;
- 60.3% are satisfied with AI use in their programme.

Among psychology teachers:

- 82.6% use AI often or always;
- 32.6% have received university training;

- 47.8% report transferring field-specific competence;
- 34.8% use AI to support students with fewer opportunities;
- 69.6% want further field-specific learning;
- 58.7% are satisfied with their AI use.

These results are based on 68 students and 46 teachers and must therefore be interpreted as exploratory.

Interpretation

The psychology profile suggests that practical adoption may be progressing faster than structured professional integration.

This is particularly sensitive because psychological applications can involve:

- highly personal data;
- assessment of mental states or behaviour;
- predictions concerning vulnerable individuals;
- automated or semi-automated mental-health support;
- emotional recognition;
- professional decisions with significant consequences.

High use without corresponding training and governance may create risks relating to privacy, bias, validity and inappropriate reliance on automated recommendations.

The comparatively low accessibility-related result among psychology teachers also deserves attention, although the small sample prevents a firm conclusion.

Pedagogical implication

Psychology and cognitive research require a strong distinction between:

- AI as a research or educational support tool;
- AI as an aid to professional judgement;
- AI as a system interacting directly with a client or patient.

The higher the potential impact on an individual's wellbeing, diagnosis or treatment, the stronger the requirement for validation, transparency and human supervision.

Students should understand that persuasive or empathic language generated by a system does not demonstrate psychological understanding, clinical competence or therapeutic responsibility.

Recommended action

The psychological-sciences and cognitive-research pathway should cover:

- behavioural-data analysis;
- psychological and neuropsychological assessment;
- cognitive modelling;
- neuroimaging analysis;

- affective computing and emotional-recognition systems;
- mental-health chatbots and digital interventions;
- validity and reliability of automated assessment;
- bias affecting cultural, linguistic and minority groups;
- privacy and informed consent;
- limits of prediction;
- professional supervision;
- crisis escalation and referral;
- boundaries between support and therapy.

Learning activities should include ethical case analysis, validation of automated interpretations, identification of misleading psychological claims and comparison between AI-supported and professionally supervised assessment.

Any pilot involving psychological support should be clearly limited to low-risk initial orientation, include direct access to qualified professionals and contain explicit crisis and escalation procedures.

The project application similarly identifies behavioural analysis, psychological assessment, mental-health applications and neuroscience as priority areas requiring ethical implementation and specialist competence.

4.6. Assessment as a common pedagogical priority

Across all disciplines, assessment is the area in which AI integration generates the greatest uncertainty.

Students and teachers are more accepting of AI for producing materials than for evaluating competence. Teachers also report strong concerns about dishonest practices and critical thinking.

The appropriate response is not to assume that all AI use constitutes misconduct. Nor is it sufficient to prohibit particular tools without reconsidering whether existing assessment methods still provide valid evidence of learning.

EduCATIA should promote assessment models that make the student's reasoning and contribution visible.

These may include:

- oral defence of submitted work;
- supervised practical tasks;
- portfolios documenting the development process;
- prompt and output logs;
- critical commentary on AI-generated material;
- comparison of different tools or approaches;
- identification and correction of errors;

- reflective explanation of what was accepted, revised or rejected;
- application to local or discipline-specific cases;
- explicit declaration of AI assistance.

Assessment criteria should evaluate judgement, verification, ethical reasoning and disciplinary understanding, not only the quality of the final product.

4.7. The role of the teacher

The results confirm that teachers are central to the transition from spontaneous AI use to educational competence.

Their role is not reduced by the availability of AI. It becomes more focused on:

- designing meaningful learning experiences;
- making competence objectives explicit;
- selecting appropriate tools and cases;
- supervising data and ethical risks;
- guiding verification and reflection;
- assessing the student’s reasoning;
- connecting fragmented information;
- ensuring inclusion;
- retaining professional responsibility.

The difference between teacher-reported transfer and student-recognised learning indicates that teachers need support in converting AI use into visible and assessable competence.

Training should therefore be practical, progressive and discipline-specific. It should include a train-the-trainer component so that capacity can be sustained and extended within each partner institution.

4.8. Inclusion and accessibility

The questionnaire identifies inclusion and accessibility as areas of existing practice and future potential.

AI may support:

- translation;
- subtitles and transcription;
- speech-to-text and text-to-speech;
- alternative formats;
- simplified language;
- personalised explanations;
- planning and organisational support;
- access for students with fewer opportunities.

However, the use of an AI tool does not automatically make an activity inclusive.

Tools should be evaluated in relation to:

- accuracy;
- language coverage;
- compatibility with assistive technologies;
- affordability;
- data protection;
- accessibility standards;
- the risk of creating new barriers.

Students with disabilities, learning difficulties and linguistic barriers should participate in the design and evaluation of inclusive AI applications.

4.9. Institutional conditions for pedagogical implementation

Pedagogical innovation cannot depend solely on individual teachers.

Universities need a supportive institutional environment that includes:

- visible and operational guidelines;
- approved or recommended tools;
- privacy and data-protection procedures;
- technical and pedagogical support;
- discipline-specific examples;
- clear assessment rules;
- mechanisms for reporting problems;
- procedures for reviewing and updating policies;
- accessible learning environments;
- monitoring of educational effectiveness.

Institutional guidance should explain not only what is prohibited, but how AI may be used responsibly.

The evidence gathered for the report supports curriculum review, differentiated teacher training, observable learning outcomes, assessment redesign and accessible educational practice.

4.10. Consolidated pedagogical framework

Academic area	Principal need identified	Main pedagogical focus	Essential safeguard
Education and pedagogy	Transform high use into explicit pedagogical competence	Instructional design, assessment, learning analytics and inclusion	Teacher responsibility, data governance and valid assessment

Medicine	Close the gap between strong demand and limited curriculum integration	Clinical reasoning, diagnostics, decision support and patient-centred applications	Patient safety, explainability, confidentiality and human oversight
Biomedical sciences and public health	Develop robust data and population-level AI competence	Biomedical analysis, epidemiology, surveillance and resource planning	Data quality, representativeness, reproducibility and health-data governance
Psychological sciences and cognitive research	Structure high adoption in an ethically sensitive field	Behavioural analysis, assessment, cognitive modelling and mental-health applications	Privacy, validity, bias, professional supervision and clear limits of automated support

4.11. Final conclusion

The questionnaire research confirms the strategic relevance of EduCATIA while refining its operational focus. Artificial intelligence is already widely embedded in the academic practices of students and teachers across the participating institutions. The central challenge is therefore not initial adoption, but the transition from widespread, fragmented and predominantly informal use towards educational and institutional maturity.

The evidence indicates that practical use has developed more rapidly than formal training, advanced competence, explicit curriculum integration, assessable learning outcomes and institutional guidance. Students and teachers recognise important benefits, but they also report uncertainty concerning reliability, critical thinking, academic integrity, assessment, data protection and professional responsibility. EduCATIA should consequently avoid both unrestricted technological adoption and generic prohibition. Its principal contribution should be to establish the human, pedagogical and institutional conditions under which AI can support learning without replacing the intellectual and professional responsibilities of students and teachers.

The project should transform existing individual practices into coherent curricula, explicit and assessable student competences, stronger teacher capacity, transparent institutional governance, ethically defensible assessment, inclusive learning opportunities, professionally relevant experience and sustainable cooperation among universities, policymakers and industry. This requires a two-level educational architecture: a common foundation of critical and responsible AI literacy, combined with discipline-specific professional pathways for education and pedagogy, medicine, biomedical sciences and public health, and psychological sciences and cognitive research.

The success of EduCATIA should not be measured solely by the number of tools introduced, courses created or participants trained. It should also be demonstrated through evidence that:

- students can select appropriate tools, verify and justify AI-supported work, identify errors and bias, and declare their use transparently;

- teachers can design, guide and assess AI-related learning through valid and ethically defensible methods;
- curriculum outcomes are explicit, observable and recognisable within each discipline;
- institutional rules are understood, applicable and regularly updated;
- personal and sensitive data, patient or client interests, and professional responsibilities are protected;
- accessibility and inclusion are strengthened rather than weakened;
- AI competence is transferred to authentic academic and professional contexts.

The European survey subsample does not provide a representative or balanced basis for ranking European and Central Asian higher education systems. The contribution of the European partners should instead be understood in terms of cooperation, methodological support, knowledge transfer and the critical adaptation of relevant frameworks and practices to the needs identified in Kazakhstan and Uzbekistan.

The principal educational purpose of EduCATIA is therefore not to make AI use more frequent, but to make it more competent, transparent, critical, inclusive and professionally responsible. The questionnaire study provides the initial diagnostic basis for this transition. Programme-level decisions should now be developed through the combined examination of the survey findings, the focus-group evidence and the structured review of the degree programmes selected for modernisation.

Source: EduCATIA revised survey analysis and disaggregated tables prepared by Simona Perone. Student questionnaire, valid N = 3,717; teacher questionnaire, valid N = 960. Project alignment is based on the EduCATIA application and its work-package and disciplinary structure.

Methodological qualification: The conclusions and recommendations are derived from descriptive and self-reported survey data. They should be complemented by the subsequent focus-group analysis, curriculum review, stakeholder consultation and evaluation of project pilots before final institutional or national policies are adopted.

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Report of the Focus Group Analysis

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1. Introduction

This report presents the qualitative analysis of the focus groups conducted within EduCATIA – Advanced Training in Artificial Intelligence Technologies for Kazakhstan and Uzbekistan, an Erasmus+ Capacity Building in Higher Education project. EduCATIA seeks to support the systematic, responsible and discipline-sensitive integration of artificial intelligence into higher education, particularly through curriculum modernisation, faculty development, institutional guidance and stronger cooperation between universities, policymakers and the professional sector. Particular attention is given to education and pedagogy, medicine and health-related disciplines, public health, and psychological and cognitive sciences.

The focus-group study is part of the on-field analysis undertaken within Work Package 2 and contributes to Deliverable D2.1. According to the project design, the qualitative component involves virtual focus groups with a multi-profile sample including academic staff, policymakers and training or professional experts. Its purpose is to identify AI-related educational gaps, implementation barriers and feasible approaches to the modernisation of the degree programmes that have been selected by the partner institutions.

This qualitative analysis builds on the preceding questionnaire study involving students and teaching staff from the participating institutions. The questionnaire findings showed the extent and distribution of AI use, self-perceived competence, previous training, institutional support, curriculum visibility, ethical concerns and perceived educational needs. They indicated that AI use is already widespread, but that its integration into teaching and learning remains uneven in terms of critical competence, explicit learning outcomes, assessment practices, institutional governance and discipline-specific preparation. The results therefore do not primarily indicate a need to encourage initial adoption. They point instead to the need to convert dispersed and often informal practices into explicit, assessable, critical and professionally relevant competences.

The focus groups provide an additional interpretative layer. Whereas the questionnaires identify recurring patterns across a comparatively large respondent population, the qualitative discussions help to examine how these patterns are experienced and understood in particular institutional, disciplinary and professional contexts (Krueger & Casey, 2015). They also make it possible to explore issues that structured questionnaire responses cannot fully explain, including the practical causes of competence gaps, barriers to curriculum revision, uncertainties surrounding academic integrity and assessment, the accessibility implications of AI, and expectations concerning human oversight, data protection and institutional responsibility (UNESCO, 2021b).

The findings should therefore be interpreted as qualitative evidence rather than as statistically representative conclusions. Individual statements are used to identify recurring concerns, contrasting perspectives and context-specific experiences (Braun & Clarke, 2006; 2021), but isolated opinions are not treated as evidence of general consensus. The analysis is intended to complement, contextualise and, where appropriate, qualify the questionnaire results (Creswell & Plano Clark, 2018). Together with the subsequent review of the selected curricula, it will contribute to evidence-based recommendations concerning curriculum content, observable learning outcomes, faculty training, assessment redesign, institutional guidance and professionally relevant applications of artificial intelligence.

2. Source material and corpus profile

The corpus available for the present analysis contains material relating to focus groups organised by Astana IT University, Kazakh National Medical University, Tashkent State Pedagogical University, Yangi Asr University, Sapienza University of Rome, Igor Vitale International and the University of Freiburg. It includes original or automatically generated transcripts, translated versions, edited and thematically reorganised transcripts, participant profiles and preliminary summary sections. The available records differ in their level of detail. Dates, moderators, participant profiles and duration are explicitly documented for some sessions, whereas other records contain incomplete metadata or combine several previously processed source files.

2.1. Concise source profiles

Focus group	Source profile
University of Freiburg (UFR)	**Country:** Germany. **Organising institution:** University of Freiburg. **Participants:** the available documentation identifies three principal contributors: an academic researcher; a university researcher who also teaches at bachelor’s level; and an external lecturer in an engineering faculty who is also active in research. **Disciplinary and professional profile:** scientific research, engineering, university teaching and applied research involving confidential or potentially patentable information. **Date, moderator and duration:** not identified in the available compiled material. **Language:** English. **Structure:** practical use of AI in research and teaching; prompting and verification; fabricated scientific references and technical hallucinations; academic integrity; privacy and intellectual property; access to paid tools; automated grading and human responsibility. **Source types:** participant profiles and a thematically organised analytical summary derived from several source files. No complete verbatim transcript has been clearly identified in the current corpus. The Freiburg material has therefore been treated as a secondary qualitative source. It is sufficiently detailed for thematic comparison, but not for analysis of exact wording, interactional dynamics or speaking frequency.

Astana IT University (AITU)	**Country:** Kazakhstan. **Organising institution:** Astana IT University. **Date:** 26 July 2026, beginning at 11:29. **Moderator:** Medet Mukushev. **Duration:** 38 minutes and 32 seconds. **Participants:** at least six named contributors in addition to the moderator, including Aigerim Kydyrbekova, Raiymbek Nurtay, Sanzhar Sovet, Anar Mengdigali, Assanali Tokenov and another participant referred to as Altunbek. Their precise institutional positions and disciplinary affiliations are not consistently specified. **Language:** Russian. **Structure:** introductory question; AI literacy and practical barriers; institutional and national governance; curriculum integration; scenario-based discussion of academic integrity, bias, privacy and automated grading; concluding synthesis. **Source type:** timestamped meeting transcript, apparently produced from an audio or video recording. It is the most direct available record and has therefore been treated as the primary source for this group.
Igor Vitale International (IVI)	**Country:** Italy. **Organising partner:** Igor Vitale International. **Date:** 19 June 2026. **Moderator:** Igor Vitale. **Logistical and documentation support:** Luca Baruffa. **Participants:** four principal discussants: an educator who was also a university student; a psychologist specialising in developmental interventions and neurodivergence; a corporate AI expert and consultant; and a trainer specialising in sports video analysis and AI applications. Fernando Martínez de Carnero was also present during introductory or organisational phases. **Language:** Italian in the original transcript. **Duration:** approximately 75 minutes, based on the timestamps contained in the original record; the exact closing time should be confirmed.

	Structure: project contextualisation; barriers to AI integration; competence gaps; institutional regulation; curriculum and assessment; ethical and policy scenarios; conclusions. **Source types:** an automatically generated Italian transcript and one or more refined English versions organised by theme. The original Italian transcript has been treated as the primary evidential source, while the edited English version has been used to support navigation and comparison.
Sapienza University of Rome	**Country:** Italy. **Organising institution:** Sapienza University of Rome. **Date:** 19 June 2026, beginning at 09:48 CEST. **Moderators:** Oleg Missikoff and Fernando Martínez de Carnero. **Participants:** seven invited experts in addition to the moderators, representing computer science, pedagogy, software and systems development, digital transformation and public administration, sociology of culture and media, educational technology, archaeology and the humanities. **Language:** Italian. **Duration:** unavailable in the current source profile. **Structure:** project objectives; diagnosis of educational and institutional gaps; curriculum and pedagogical change; academic assessment; governance and ethics; practical recommendations. **Source type:** refined transcript organised into thematic blocks, incorporating oral contributions and comments written in the chat. In the absence of a clearly identified original transcript in the current corpus, this refined version has been used as the primary source, but quotations and fine-grained linguistic interpretations should be treated cautiously.

Kazakh National Medical University (KazNMU)	**Country:** Kazakhstan. **Organising institution:** S. D. Asfendiyarov Kazakh National Medical University. **Moderator:** Saltanat Mamarbekova. **Coordination and facilitation:** Laura Beizbekovna. **Participants:** the transcript indicates six participants at the beginning of the discussion, although the accompanying profiles identify a broader set of contributors or individuals involved in the session documentation. Profiles include senior academic leadership, faculty members, an epidemiologist and public-health researcher, a developer or programmer, and healthcare management and MBA educators. **Disciplinary profile:** medicine, public health, epidemiology, healthcare management, programming and institutional leadership. **Duration:** planned for approximately 90 minutes and reported to have exceeded the intended schedule by around three minutes. **Date:** not identified in the available text. **Language:** Russian. **Structure:** current use of AI in research, administration and teaching; risks to foundational and clinical competence; assessment; curriculum organisation; institutional resources; ethics, confidentiality and professional responsibility. **Source types:** translated transcript, participant-profile table and executive summary. The translated transcript has been treated as the primary source; the executive summary is considered a secondary analytical document rather than independent evidence.

Yangi Asr University (YAU)	**Country:** Uzbekistan. **Organising institution:** Yangi Asr University. **Participants:** the available materials identify at least four teaching staff members, including a lecturer, a teacher, an acting associate professor specialising in special pedagogy and another faculty member. The broader discussion appears to include academic staff from pedagogical and other disciplinary areas. **Date, moderator and duration:** not available in the compiled material. **Language:** Russian. **Structure:** teacher preparedness; reliability and verification of AI outputs; institutional rules; student disclosure of AI use; assessment redesign; human oversight and approval of educational tools. **Source types:** participant profiles and thematic summary derived from several source files. Because no complete original or verbatim transcript has been clearly identified, the YAU material has been treated as a secondary qualitative source. Findings from this group are included where they are explicit and recurrent, but they are not used for detailed quotation or analysis of interactional dynamics.

All documents have been transcribed into English.

2.2. Source hierarchy and analytical use

Where several versions of the same session were available, priority was given to the document closest to the recorded discussion. The source hierarchy applied in the analysis was:

Edited transcripts were useful for identifying topics and locating relevant passages, but they were not treated as equivalent to verbatim records. Editing may remove repetitions, interruptions, uncertainty, disagreement or moderator influence and may combine several interventions into a more coherent formulation than appeared in the discussion itself. Similarly, preliminary executive summaries were treated as interpretations prepared after the sessions rather than as additional participant evidence.

The University of Freiburg evidence was drawn from participant profiles and a structured thematic synthesis because no complete original transcript was clearly identifiable in the compiled corpus. It was therefore used to identify substantive topics and institutional concerns, but not for detailed quotation or interactional analysis.

3. Questionnaire findings relevant to curriculum modernisation

3.1. Current use of AI by students and teachers

AI use was widespread in both respondent groups. Only 7.6% of students reported never using AI for their studies, while 44.9% used it often or always. Among teachers, 7.1% reported no use in teaching, whereas 48.3% used AI often or always. AI can therefore no longer be treated as a marginal or prospective element of university education within the participating institutions.

The purposes reported were diverse. Students used AI particularly for tutoring and explanations, translation, data analysis, accessibility and the production of study resources. The most frequently selected applications included tutoring and study support, reported by 78.7%, translation by 75.1%, data analysis by 69.7%, and mind maps or related study aids by 59.8%. Teachers also reported broad use, particularly for translation, presentations, assignment preparation and other teaching-related tasks. Translation was reported by 75.0%, presentation creation by 63.5%, and assignment creation by 61.9%.

This breadth of use has two main curricular implications. First, modernisation should begin from practices that are already familiar to students and staff rather than from abstract introductions to AI. Second, familiarity with particular tools should not be treated as equivalent to educational competence. Existing use needs to be connected to learning objectives, disciplinary standards, verification procedures and transparent assessment.

The similarity between proportions of frequent users among students and teachers also suggests that AI is not entering universities exclusively through either student initiative or teaching reform. It is developing simultaneously across both groups, although not necessarily through coordinated educational processes.

3.2. AI knowledge and previous training

Advanced self-perceived knowledge remained uncommon. Approximately 7% of both students and teachers described their AI knowledge as advanced. The use of paid tools was also limited, reported by 21.5% of students and 27.4% of teachers. These findings suggest that broad participation is based predominantly on functional use of widely available systems rather than on advanced technical or professional mastery.

Formal university training had reached 36.3% of students and 49.4% of teachers. Institutional capacity-building appears, therefore, to have prioritised academic staff to some extent, but it had still not reached approximately half of the teachers or almost two thirds of the students.

Demand for further learning was considerably higher than previous participation in training. Among teachers, 81.2% expressed an interest in learning more about AI in general, while 79.9% wanted to acquire additional competences relating specifically to their teaching field. Interest remained high among teachers who had already completed university-organised training, indicating that professional development should be continuing and progressively specialised rather than limited to a single introductory course.

Training was associated with more developed reported practice. Teachers who had participated in university-organised training were more likely to use AI often or always, report advanced knowledge, transfer general and field-specific competences, support students with fewer opportunities and express satisfaction with their use of AI in comparison to untrained teachers. For example, 78.5% of trained teachers reported transferring general AI competences, compared with 50.0% of teachers without such training.

This relationship is descriptive and does not establish that training alone caused the differences. Teachers with greater prior interest or stronger institutional support may have been more likely to participate. Nevertheless, the findings support the inclusion of structured faculty development as a central condition of curriculum modernisation.

Training should distinguish at least three levels of competence: basic functional literacy; pedagogical use and assessment design; and discipline-specific professional application. A single general course is unlikely to address all three adequately.

3.3. Institutional support and guidance

Institutional provision was substantially less developed than individual use. Some form of university AI guidance was recognised by 48.0% of students and 48.9% of teachers. The close correspondence between the two groups suggests that approximately half of the respondents either lacked visible guidance or were unaware that such guidance existed.

The questionnaire did not independently verify institutional policies. Respondents may have understood *guidelines* to include university regulations, faculty instructions, course-level rules, academic-integrity provisions or informal recommendations. The result should therefore be interpreted as a measure of perceived availability and visibility rather than as a formal policy audit.

Responses concerning the clarity of guidance also contained inconsistencies. Some respondents who initially reported that no guidance existed subsequently assessed its clarity, while others reported its existence but later selected an option indicating that there were no guidelines. These inconsistencies may reflect uncertainty about what constitutes official guidance and where institutional responsibility is located.

For curriculum modernisation, the relevant issue is not merely whether a general policy document has been issued. Guidance needs to be visible at programme and module level and should clarify permitted uses, disclosure and citation requirements, data protection, responsibility for outputs, acceptable support in assignments, and the conditions under which AI may be used in assessment (European Commission, 2022).

General institutional principles should be supplemented by disciplinary protocols. The risks associated with translation support or lesson planning are not equivalent to those arising from clinical decision-making, psychological assessment or the processing of sensitive personal data.

3.4. Transfer of AI competences

The most important discrepancy between the student and teacher questionnaires concerns competence transfer. Among teachers, 64.1% stated that they transferred general AI competences to students and 72.0% reported transferring field-specific competences. By contrast, only 31.7% of students stated that they had learned AI skills from their professors.

These results do not measure exactly the same educational interaction. The student and teacher respondents were not linked at course level, and the questions were worded differently. The discrepancy cannot therefore be interpreted as direct evidence that teachers overestimated their activity.

Nevertheless, its scale is educationally significant. It suggests that AI may be used or demonstrated by teachers without always becoming an explicit and recognisable student competence (UNESCO, 2021a). This can occur when learning outcomes are not clearly formulated, practice opportunities are limited, feedback is not provided or AI-related performance is not assessed.

The transfer gap indicates that curriculum modernisation should not be measured simply by whether teachers use AI or mention it during their courses. Students should be able to identify what competence they are developing, practise it in relevant tasks and demonstrate it through observable outcomes.

AI-related learning outcomes should therefore use assessable formulations. Depending on the academic level and discipline, students may be expected to compare AI-generated outputs with authoritative sources, document how a system was used, identify errors or bias, justify the selection of a tool, protect sensitive data or explain when human judgement must override an automated recommendation.

3.5. Ethical attitudes, risks and academic integrity

Ethical acceptance varied according to the purpose of AI use and the academic role involved. Among students, 65.5% considered it fair to use AI in completing assignments, while 64.7% accepted teachers' use of AI to create educational materials. Acceptance fell to 48.9% for the use of AI by teachers to assess student competence.

Teachers were more accepting of their own use of AI: 79.5% considered its use for creating educational content fair, and 63.1% accepted its use in assessment. Only 56.1%, however, regarded student use of AI for assignments as fair. Assessment was therefore the area of greatest sensitivity for both groups.

Teachers' concerns were especially pronounced. Reliability of AI-generated information concerned 84.4%; possible negative effects on students' critical thinking concerned 82.9%; and increased dishonest practices concerned 79.5%. Concern about the replacement of professors, at 40.6%, was substantial but considerably less widespread.

The pattern shows that the principal perceived risks are pedagogical and ethical rather than centred exclusively on employment displacement. Teachers are concerned about whether students can evaluate AI-generated material, retain intellectual independence and complete work whose authorship and learning value can be established.

Students reported a more mixed experience. A majority believed that AI helped them learn more quickly and effectively, but 36.1% agreed that it had reduced their critical thinking. More frequent users tended to report both greater benefit and greater perceived cognitive risk.

These findings support the inclusion of critical verification, source evaluation, bias detection, academic integrity and transparent disclosure as core curriculum elements (Miao & Holmes, 2023). They also indicate a need to redesign assessment. Policies based exclusively on prohibition or detection are unlikely to be sufficient where AI is already widely used and where acceptance varies according to the nature of the task.

Assessment should make students' reasoning more visible through staged submissions, oral explanation, reflective accounts, source comparison, supervised practice or the documentation of AI-supported workflows. The objective is not to make every task technically impossible for AI to complete, but to ensure that student judgement and disciplinary competence remain assessable.

3.6. Accessibility and inclusion

Accessibility emerged as an established use case rather than a purely prospective application. Approximately 62.5% of students reported using AI for accessibility-related purposes, while 56.6% of teachers used it in this area. In addition, 62.9% of teachers stated that they used AI to improve access for students with fewer opportunities. Relevant applications may include transcription, subtitles, text-to-speech and speech-to-text systems, translation, simplified explanations, alternative formats, study organisation and multilingual support. These applications are particularly relevant within an international project operating across several languages and educational contexts.

Accessibility should therefore be included within core AI literacy and faculty training rather than treated solely as a specialist or optional topic. Teachers and students need to understand both the potential and the limitations of compensatory technologies.

The presence of an accessibility function does not in itself make a tool inclusive. Accuracy, cost, interface design, linguistic coverage, privacy and access to suitable devices may create new barriers. Curriculum and pilot development should therefore include user testing with students who have disabilities, learning difficulties, linguistic barriers or fewer opportunities.

Interest in AI-supported university services was also considerable. More than half of students expressed interest in applications relating to administrative tutoring, internship support, AI-generated lessons and initial psychological support. This supports controlled experimentation, but risk levels differ substantially. Administrative and orientation services may provide appropriate initial pilots, whereas psychological support and applications involving sensitive information require clear limits, professional supervision and escalation procedures.

3.7. Discipline-specific findings

The disciplinary results show that institutions and academic areas are not positioned along a single continuum from low to high AI maturity. Different groups combine adoption, training, competence transfer and demand in different ways.

The two largest student groups were medicine, with 1,469 respondents, and education, with 1,291. Education students reported more frequent use, greater participation in university training and stronger recognised curriculum integration. Among education students, 48.6% used AI often or always, 40.9% had attended university training, 41.3% reported learning AI skills from professors and 41.2% identified field-specific AI teaching in their programmes.

Among medicine students, the corresponding figures were 43.2% for frequent use, 36.0% for training, 21.8% for learning from professors and 27.4% for field-specific teaching. However, interest in additional field-related AI competence was much higher in medicine (78.4%) than in education (55.1%).

This indicates a particularly visible gap between demand and formal provision in medicine. Curriculum development in this area should not be limited to general generative-AI literacy. It should address professionally relevant uses while maintaining strong requirements concerning evidence, patient safety, data protection, explainability and human responsibility.

Education presents a different profile. AI is more visible in current learning and teaching practices, but frequent use creates an immediate need for pedagogical frameworks covering adaptive support, material production, learning analytics, assessment and the preservation of student agency.

Teacher results support this distinction. Teachers classified within medicine and health sciences reported comparatively low frequent use, at 33.9%, but relatively strong field-specific competence transfer, at 74.9%, and accessibility-related support, at 65.7%. Teachers in the broader education, psychology and social-sciences category reported much more frequent use, at 72.9%, but lower field-specific transfer, at 63.5%, and lower accessibility-related use, at 51.0%.

Psychology teachers reported very frequent use but comparatively limited training, structured competence transfer and accessibility-related application. Since the subgroup included only 46 respondents, this pattern should be interpreted cautiously. It nevertheless identifies issues to examine through the focus groups and curriculum review, particularly privacy, validity, bias, automated assessment and the limits of AI-supported mental-health interventions.

The biomedical-sciences sample was also small, and public health could not be isolated fully through the questionnaire categories. Findings for these fields are therefore exploratory. Their needs should be specified using the curriculum documents, focus-group evidence and consultation with the relevant institutions.

Reliability was a transversal concern. It was reported by 83.9% of teachers in medicine, 87.2% in education, 87.0% in psychology and 83.6% in other areas. Verification should consequently form part of the common curriculum foundation, even though its practical meaning differs by discipline.

3.8. Main implications for curriculum development

The questionnaire evidence supports a two-level curriculum architecture.

The first level should provide a common foundation in critical and responsible AI literacy. This foundation should include the basic operation and limitations of AI systems, prompt formulation, output verification, source evaluation, bias, privacy, academic integrity, transparency, accessibility and human oversight.

The second level should consist of discipline-specific pathways. These should connect AI competence to authentic professional tasks, relevant data, disciplinary standards and sector-specific responsibilities.

Curriculum priority	Questionnaire basis	Curriculum response
Make AI learning explicit	Widespread use but limited recognised curriculum integration	Introduce identifiable learning outcomes, taught activities and assessment criteria

Strengthen faculty capacity	High demand for further teacher training and stronger reported practice among trained teachers	Provide continuing development in pedagogy, assessment and disciplinary application
Address the transfer gap	64.1–72.0% teacher-reported transfer compared with 31.7% student-recognised learning	Make competences visible, practised, assessed and communicated to students
Redesign assessment	Selective ethical acceptance and strong concern about integrity and critical thinking	Use authentic, process-based and transparent assessment with appropriate disclosure
Develop institutional guidance	Only around half recognised AI guidelines	Link university policy to programme, module and disciplinary rules
Embed inclusion	Accessibility-related use was reported by more than half of both groups	Integrate accessibility, multilingualism and user testing into courses and pilots
Differentiate by discipline	Contrasting profiles in medicine, education and other fields	Develop profession-specific content, safeguards and applications
Evaluate competence, not adoption alone	Frequent use coexists with low advanced knowledge	Assess verification, judgement, ethical reasoning and professional application

Curriculum modernisation should not be evaluated solely through the number of new modules, tools or training participants. It should also establish whether students can verify and justify AI-supported work, whether teachers can design and assess relevant learning, whether institutional rules are understood, whether sensitive information is protected and whether competence can be transferred to professional contexts.

The questionnaire-based conclusion is therefore that the participating institutions display broad AI adoption but uneven educational and institutional maturity. The task for EduCATIA is to transform existing individual practices into explicit, critical, ethical, inclusive and discipline-specific competences.

4. Focus-group findings

4.1. Overview of the focus-group evidence

The qualitative corpus brings together focus-group material from higher education institutions and project partners in Kazakhstan, Uzbekistan, Italy and Germany. The sessions represented academic teachers, researchers, institutional leaders, information-technology specialists and professionals working in education, psychology, medicine, public health, digital administration and applied AI-related fields.

The groups were not identical in size, composition or documentation. Some sessions brought together participants from several disciplines, while others were more closely associated with a particular institutional or professional context. The available material also varies between timestamped transcripts, translated transcripts, refined thematic versions and summary reports. These differences limit direct comparison of speaking frequency or exact wording, but the corpus provides sufficient substantive evidence to identify recurring concerns, contrasting positions and context-specific needs.

The principal institutional sources considered in the analysis were:

Country	**Institution or partner**	**Main profiles represented**
Kazakhstan	Astana IT University	University teachers and experts with experience of AI, information technology, assessment and institutional governance
Kazakhstan	Kazakh National Medical University	Medical and public-health academics, researchers, institutional leaders, healthcare-management specialists and technical staff
Uzbekistan	Tashkent State Pedagogical University	Teachers and researchers in psychology, languages, information technology, pedagogy and special education
Uzbekistan	Yangi Asr University	Lecturers and academic staff from pedagogical and related disciplinary areas
Italy	Sapienza University of Rome	Academics and professionals from computer science, pedagogy, digital administration, sociology, educational technology, archaeology and the humanities
Italy	Igor Vitale International	Education, psychology, neurodivergence, corporate AI and applied professional training
Germany	University of Freiburg	Researchers and lecturers with experience in scientific research, engineering, data protection and university teaching

Across the groups, the discussion concentrated on current AI use, competence gaps, curriculum integration, assessment, academic integrity, institutional rules, privacy, inclusion and professional relevance. Several sessions also used scenarios concerning AI-generated student work, automated grading, discriminatory decision-making and the use of external platforms.

The evidence should be interpreted as a set of informed qualitative perspectives rather than as a representative account of all participating institutions. The groups provide particular value in explaining why widespread AI use has not yet been converted consistently into explicit educational competence or institutional practice.

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4.2. Current practices and experiences with AI

Participants described AI as already embedded in many aspects of academic work. Its use was generally presented as routine and dispersed rather than formally coordinated. Teachers reported using generative systems for preparing presentations, drafting or adapting teaching materials, creating exercises, structuring syllabi and producing preliminary versions of administrative or regulatory texts. In some groups, AI was also used to create test questions, provide initial feedback on student work or identify structural problems before manual review. This matches the data provided in the previously introduced quantitative analysis (see: chapter **4.3 Current use of AI by students and teachers**).

The Kazakh National Medical University discussion provided particularly detailed examples of academic and administrative use. Participants referred to drafting curriculum concepts and institutional documents, accelerating literature searches, screening scientific publications and supporting data-analysis tasks. AI was also used to generate or translate code between statistical environments and to conduct initial reviews of manuscripts or student assignments. These applications were valued primarily for reducing time spent on preparatory or repetitive work.

Research use was also prominent in the University of Freiburg and Italian groups. Participants described AI as potentially useful for summarising complex material, structuring ideas, analysing technical information, searching patent literature, supporting programming and making difficult concepts more accessible. However, the benefits depended heavily on the user's ability to verify the result and on whether the system was connected to reliable sources.

The distinction between **general-purpose chatbots and controlled environments** was particularly visible in the IVI group. One professional participant argued that closed systems based on selected and verified documentation could substantially reduce hallucinations compared with open conversational tools. Other participants agreed that such systems could improve reliability, but emphasised that they still required careful configuration, testing and human supervision. The evidence therefore does not support a simple contrast between unreliable public tools and fully reliable institutional systems. Rather, it suggests that reliability depends on data provenance, tool design, user methodology and ongoing validation.

Student use was usually discussed from the perspective of teachers and experts rather than directly reported by a large number of students. Participants described students using AI to draft essays, complete homework, produce presentations, translate texts, generate code and answer questions. In several groups, concern centred on direct submission of generated material without meaningful review. Teachers reported recognising repetitive structures, uniform answers and work that students could not subsequently explain.

At Astana IT University, one participant described creative assignments producing almost identical responses across an entire class because students had relied on similar AI systems. The result was not only a concern about authorship but also a loss of the diversity that the task had been designed to elicit. Other participants reported that students frequently treated AI output as a finished answer rather than as material requiring checking, revision or interpretation. The given information interacts meaningfully with the results of the questionnaire regarding concerns in assessment procedures from the point of view of the teachers (see: chapter **3.5. Ethical attitudes, risks and academic integrity**).

In language teaching, participants observed extensive reliance on machine translation. This could support comprehension and multilingual access, but it could also weaken active vocabulary, grammar and independent writing when used as a substitute for language production. In psychology and pedagogy, concern focused on students reproducing generic formulations that resembled analysis but did not demonstrate empathy, contextual judgement or conceptual depth. In technical subjects, participants mentioned generated code that appeared functional but contained methodological or logical errors.

Professional applications differed substantially by field. Medical participants referred to diagnostic-support systems, data analysis, research screening and healthcare administration. They generally accepted that AI would become part of professional practice, but distinguished clearly between decision support and autonomous decision-making (World Health Organization, 2023) -this also reflects the uses reported in the questionnaire results and matches the needs identified for the improvement of the medicine curricula in **3.7. Discipline-specific findings**. In education, participants discussed adaptive materials, tutoring, assessment support, accessible formats and learning design. In psychology, potential applications included behavioural analysis and support tools, although participants expressed strong concern about confidentiality, validity and the danger of replacing professional interaction. Technical and business-oriented participants referred to coding, patent analysis, document production, process optimisation and data-supported decision-making.

A recurring distinction across the groups was between **spontaneous use and formal educational integration**. AI was often adopted because individuals found it useful, not because its use was linked to explicit learning outcomes, approved tools, programme-level guidance or coordinated assessment. Teachers frequently experimented independently, and students developed practices through informal peer networks or publicly available systems.

This distinction is central to the qualitative findings. The groups did not describe universities where AI was absent. They described institutions in which use had advanced faster than the educational and organisational structures required to govern it. The problem was therefore framed less as technological access than as the quality, visibility and consistency of integration.

4.4 AI literacy and competence gaps

Participants used the concept of AI competence in a broad sense. It included basic understanding of what AI systems can and cannot do, the ability to formulate an appropriate request, the capacity to verify outputs, awareness of bias and privacy, and the professional judgement required to decide whether an output should be used.

Basic understanding was uneven. Several participants suggested that both students and teachers used AI without understanding how probabilistic systems generate responses, why outputs may differ between prompts or why a fluent answer is not necessarily a reliable one. This created what some participants described as an illusion of competence: users obtained sophisticated-looking results and interpreted their ability to produce them as evidence of subject mastery.

Prompting was repeatedly identified as a practical gap. Participants observed that brief, vague or poorly contextualised prompts produced weak results, but they did not treat prompt engineering as an isolated technical skill. Effective prompting requires the user to define the problem, establish constraints, specify the intended audience, select suitable sources and evaluate whether the output addressed the original purpose.

In the IVI group, participants emphasised that useful AI interaction often required multiple iterations and a structured workflow. Users needed to refine the request, identify errors, supply additional information and decide when the system should not be trusted. The discussion challenged the assumption that AI necessarily saved time. For inexperienced users, or for high-stakes academic work, developing and checking an adequate output could require considerable effort.

Verification was the most consistently required competence across the corpus. Participants referred to incorrect numerical claims, fabricated references, invented authors, invalid digital object identifiers, non-existent chemical structures, unsuitable clinical recommendations and questions that did not correspond to the taught syllabus. The University of Freiburg group was particularly concerned about fabricated scientific literature and technically plausible but incorrect information in specialised fields.

Verification of AI performance was also presented as a competence gap in some cases. At Astana IT University, a participant described teachers using AI to generate hundreds of examination questions without checking each item individually. The resulting tests could include content that had not been taught or that did not match the syllabus. This example illustrates that AI literacy is not only a student issue. Inadequate faculty verification may affect curriculum alignment, assessment validity and the fairness of educational decisions.

Participants frequently used the term *hallucination* to describe confident but inaccurate output. Their concern included not only factual errors in AI responses, but also the persuasive style of AI systems when providing incorrect information.

Well-structured language, apparent certainty and detailed explanation could make incorrect information more difficult to recognise, especially for users without sufficient disciplinary knowledge.

In this respect, the focus group also linked AI competence to prior subject knowledge. A student cannot reliably evaluate an AI-generated explanation of medicine, psychology, engineering or history without a foundation against which to judge it. AI literacy cannot replace disciplinary education; it depends on it. This was one reason why some participants favoured more limited and supervised use during the early stages of a degree and greater autonomy after students had developed conceptual foundations.

Critical thinking was treated as both a required competence and a potentially threatened educational outcome. Participants did not claim that AI inevitably reduces critical thinking. They argued that the effect depends on task design and patterns of use. AI may weaken critical reasoning when it supplies finished answers that students reproduce without analysis. It may support critical reasoning when students are required to compare outputs, identify inconsistencies, verify sources, improve arguments or explain why a recommendation is unsuitable. This also interacts with the results of the quantitative questionnaire in the sections related to critical thinking from the teachers' point of view (see: **3.5. Ethical attitudes, risks and academic integrity**).

This distinction was especially important in the Sapienza group. Participants argued that the teacher's task was not to compete with AI as a source of information, but to design learning experiences in which students had to connect ideas, evaluate alternatives and construct a coherent understanding. AI could provide fragments or initial suggestions, but the teacher remained necessary to organise and contextualise learning.

Bias detection appeared in discussions of admissions, scholarships, medicine, psychology and the representation of different cultural contexts. Participants recognised that AI models may reproduce historical inequalities, underrepresent particular populations or generate recommendations based on data that do not match local conditions.

Kazakh medical participants were particularly concerned that systems trained predominantly on Western datasets might produce advice that did not reflect Kazakhstan's healthcare infrastructure, social context or clinical resources. This was not presented simply as a national preference. It concerned the validity and applicability of evidence. A technically accurate recommendation may still be inappropriate when the underlying assumptions, population or available resources differ.

The evidence supports a definition of critical AI literacy that goes beyond operational use. The central competence is the ability to formulate an appropriate problem, interrogate the output, verify its evidential basis, recognise bias or uncertainty, contextualise the result and decide when it should be modified or rejected.

4.5 Curriculum integration

The current presence of AI in formal curricula varied substantially. **Technical programmes** were more likely to include machine learning, programming, data analysis or related computational content. However, participants frequently reported that ethical, pedagogical, legal and professional dimensions remained underdeveloped even where technical AI content existed.

At Astana IT University, participants noted that bachelor's and master's programmes covered machine learning and practical applications, but that responsible use, ethics and data security were less visible. The group argued that technical students should not graduate with the ability to build or apply systems but without understanding bias, privacy, explainability and accountability.

In **non-technical fields**, participants generally rejected the idea that curriculum integration should be limited to prompt-writing workshops. They emphasised transversal competences such as critical evaluation, source verification, data protection, transparent disclosure and human oversight. These should then be connected to disciplinary applications.

The Sapienza group framed curriculum modernisation as a wider pedagogical issue. Some participants argued that universities remained organised around relatively static content-transmission models that were poorly adapted to rapid technological and professional change. From this perspective, simply adding a new AI module would be insufficient. Curriculum reform should also strengthen problem-solving, interdisciplinary work, active learning and the capacity to respond to changing knowledge environments.

Two alternative models of curriculum integration appeared across the groups. The first involved dedicated AI modules covering basic concepts, prompting, verification, ethics and data governance. The second involved embedding AI across existing subjects and years of study. Participants did not necessarily treat these approaches as mutually exclusive.

Kazakh National Medical University participants generally supported pervasive integration across the medical curriculum rather than locating AI within a single department. They argued that students should encounter relevant applications in the context of diagnostic reasoning, research, epidemiology, healthcare management and clinical decision-making. A common introductory foundation could be useful, but professional competence needed to develop repeatedly through subject-specific practice.

A similar progression was proposed in the Sapienza material. Early undergraduate education could place stronger limits on unsupervised AI use while students acquired conceptual foundations. Later stages could integrate AI as a tool for co-design, analysis and complex problem-solving. This approach seeks to avoid both extremes: complete prohibition and unrestricted use before students can evaluate the result.

Participants also identified **discipline-specific curriculum possibilities**. Tashkent State Pedagogical University contributors proposed content on the psychology of human–AI interaction, particularly for psychology and education students. Technical students were considered to need practical work on prompting, security, vulnerabilities and ethical implementation. Language programmes needed to distinguish between translation as support and translation as a substitute for active language production.

In medicine and public health, relevant areas included clinical decision support, diagnostic imaging, research analysis, epidemiological modelling, patient-data protection and professional responsibility. Participants emphasised that such content should be based on realistic cases and should train students to reject unsafe or contextually inappropriate recommendations.

Psychology-related discussions focused less on technical model construction and more on professional boundaries, validity, empathy, data sensitivity and the risks of automated interpretation. Participants were concerned about uploading psychological tests, case material or personal data to external systems. They also questioned whether tools designed for broad populations could be used safely with neurodivergent people or individuals in vulnerable circumstances.

Several **administrative and curricular barriers** were identified. Participants described formal programme approval as slow relative to technological change. Departmental boundaries could make interdisciplinary courses difficult to authorise, while national or institutional standards sometimes limited rapid syllabus revision. At Astana IT University, one participant argued that teachers needed greater capacity to update course content during the academic year because the relevant tools and practices changed over periods shorter than normal curriculum-review cycles.

The Tashkent State Pedagogical University material similarly referred to bureaucratic delays in changing state curriculum standards. Participants favoured greater departmental autonomy to adapt teaching methods and assessment structures without waiting for complete programme reapproval.

At Kazakh National Medical University, the barrier was also connected to internal educational structures. Participants criticised curricula organised partly around credit allocation and departmental workload rather than learning outcomes and professional need. They argued for a stronger outcome-based approach that would make it easier to integrate AI where it contributed to clinical, research or public-health competence.

The overall evidence suggests that curriculum integration requires both stability and flexibility. Core principles—verification, responsibility, privacy, critical thinking and professional judgement—are sufficiently durable to support formal learning outcomes. Tool-specific content, examples and workflows require mechanisms for more frequent revision.

4.6 Assessment and academic integrity

Assessment was the most consistently contested area in the focus groups. Participants agreed that AI had weakened the validity of some conventional **take-home tasks**, particularly essays, written reflections, standard problem sets and unsupervised presentations. The problem was not simply that AI could generate text. It was that educators could no longer assume that the final product demonstrated the student's reasoning or authorship.

Teachers described a widening difference between polished take-home work and students' performance under supervision. At Kazakh National Medical University, participants reported that students could achieve very high results on AI-assisted homework but perform poorly in proctored examinations. This discrepancy was interpreted as evidence that the submitted product did not necessarily reflect retained knowledge or independent competence.

Tashkent State Pedagogical University participants described similar concerns. Some reported moving a substantial proportion of assessment towards classroom-based writing, oral discussion, live case analysis and project-based work. Mandatory oral defence was proposed as a way to require students to explain the reasoning, argument or code underlying a submitted product.

The groups generally rejected complete prohibition as impractical. Participants distinguished between AI replacing the central intellectual work of an assignment and AI supporting limited stages such as brainstorming, grammar correction, translation, initial structuring or comparison. The difficulty lay in defining and communicating this boundary.

Transparency was therefore a recurring proposal. Students should declare whether AI was used, identify the tool and describe its role. In more advanced tasks, they might also document prompts, revisions, sources checked and decisions made. Participants did not propose that disclosure alone would make every use acceptable. It was treated as a condition for evaluating whether the use was proportionate to the learning outcome.

One formulation emerging from the Sapienza discussion was that AI use should be legitimate when it is declared, traceable and followed by a student's capacity to justify the result orally. This principle combines transparency with demonstrated understanding and avoids treating authorship as a purely technical detection problem.

Automated AI detectors were viewed sceptically. Participants referred to false positives, inconsistent classifications and the risk of accusing students without reliable evidence. At Astana IT University, contributors argued that punishment was particularly problematic where no clear written rule existed. A student should not be penalised retrospectively for conduct that had not been defined as prohibited.

The groups therefore did not regard detection software as an adequate foundation for academic-integrity policy. Detection might provide a weak signal or support further review, but it should not replace evidence, dialogue or professional judgement. Overreliance on detectors could also divert attention from the more important task of redesigning assessment.

Several alternatives were proposed: staged submissions, oral defence, reflective commentary, portfolios, classroom-based analysis, group discussion, project-based learning and comparison between AI-assisted and non-AI approaches. These methods seek to make the process visible rather than relying exclusively on the final product.

Participants also highlighted the continuing **value of supervised or AI-free assessment** in selected circumstances. The purpose was not to recreate an artificial world in which AI did not exist, but to establish whether students had acquired foundational knowledge and could perform independently when professional responsibility required it.

Medical participants considered independent competence essential because future practitioners may need to recognise when a system is wrong or unavailable. Language teachers similarly argued that students needed to demonstrate unaided linguistic production before using AI extensively for editing or translation. In early stages of study, temporary restrictions could therefore serve a developmental function.

There was strong convergence on **human oversight in grading**. Participants accepted that AI could help create rubrics, identify anomalies, organise feedback or perform preliminary analysis. They rejected the idea that it should hold final authority over a student's grade. This interacts positively with the concerns expressed in the quantitative questionnaire on the students' side about teachers' use of AI for assessment (**3.5. Ethical attitudes, risks and academic integrity**).

The automated-grading scenarios produced some of the clearest agreement in the corpus. Participants argued that students must have access to human review and that teachers or authorised academic bodies must retain the power to modify automated recommendations. Context, error, ambiguity and individual circumstances could not be delegated fully to a system. This principle applied both to routine university assessment and to high-stakes professional education.

4.7 Ethics, privacy and data governance

Ethical discussion extended beyond academic misconduct. Participants addressed personal-data protection, research confidentiality, intellectual property, discrimination, consent, transparency and the allocation of responsibility when AI contributes to a decision.

Data protection was a major concern in the University of Freiburg, Tashkent State Pedagogical University, Kazakh National Medical University and Astana IT University material. Participants worried that students and teachers entered personal, institutional or confidential information into commercial platforms without understanding how it might be stored or reused.

Examples included student records, psychological test material, patient information, unpublished research, peer-review manuscripts, patentable ideas and internal university documentation. The risk was not limited to deliberate disclosure. Users might upload information because free tools were convenient and no approved alternative was available.

European participants referred more explicitly to formal data-protection frameworks, but they did not consider regulation alone sufficient. They distinguished between the existence of legal principles and the ability of ordinary teachers or students to apply them in practice. The proliferation of documents and the complexity of institutional responsibilities could make guidance difficult to use.

Central Asian participants more often described low awareness and limited operational guidance. At Astana IT University, one contributor observed that neither staff nor students consistently considered data collection or leakage when using free platforms. Participants favoured institutional approval of tools and clearer information about what data could be entered.

The focus groups therefore support a governance approach based on approved use cases rather than abstract warnings. Institutions need to identify which tools may be used, for which purposes, with what categories of data and under whose responsibility. Where sensitive information is involved, locally controlled, enterprise or otherwise protected environments may be necessary.

Transparency was discussed at several levels. Students should disclose AI use in assessed work. Teachers should inform students when AI contributes to teaching materials, feedback or assessment. Universities should explain when AI systems are used in administrative or student-support services. Users should also be able to understand the basis and limits of consequential automated decisions (European Parliament & Council of the European Union, 2024).

Bias was explored through scenarios involving scholarships, admissions and professional applications. Participants agreed that historical data could reproduce unequal treatment. They differed, however, in how they interpreted responsibility. One participant initially described discriminatory output as a technical implementation defect, while others emphasised the governance responsibility of the institution deploying the system.

There was also disagreement about whether human or algorithmic bias was easier to accept. One participant argued that a machine error might be easier to forgive because it lacked intent. A contrasting view was that human bias was easier to locate and challenge, whereas algorithmic bias was distributed across data, model design and institutional deployment. The disagreement is analytically useful: it shows that ethical training should address not only the existence of bias but also how accountability is assigned.

Consent emerged most clearly in relation to external platforms. Participants questioned whether a teacher should require students to create accounts on systems that collect personal data. Some considered data collection an ordinary condition of digital life, but still argued that compulsory educational use required institutional authorisation and suitable alternatives.

Professional responsibility was non-negotiable in the medical and assessment discussions. AI could inform a decision but could not bear legal, ethical or professional responsibility for its consequences (Council of Europe, 2024). Medical participants warned that uncritical use might contribute to defensive medicine or inappropriate diagnostic escalation. A system could recommend additional imaging, for example, without accounting adequately for cost, availability or patient context.

The principle of human responsibility did not mean that AI had no legitimate role. It meant that the responsible professional needed to understand the basis of the recommendation, evaluate its suitability and remain accountable for the final decision (OECD, 2024).

4.8 Institutional preparedness and faculty development

Participants generally described institutional preparedness as uneven. Some universities had policies, training activities or technical initiatives, but these were not always sufficiently visible, coherent or connected to daily teaching decisions. These discrepancies had also been identified in the quantitative questionnaire (see: **3.3. Institutional support and guidance**).

At Astana IT University, participants reported a lack of explicit common criteria. Faculties or individual teachers could respond differently to the same issue, especially in relation to student use and assessment. National investments in AI infrastructure and legislation were recognised as strategically important, but participants did not yet perceive a direct effect on everyday teaching or research.

The Yangi Asr University material similarly emphasised the absence of uniform rules and the limited practical readiness of teachers. Participants identified the need for clear guidance on student disclosure, verification and human oversight. They also suggested that regulation should be accompanied by practical examples rather than issued only as general principles.

European groups did not present institutional maturity as complete. Sapienza participants distinguished between broad public or European frameworks and the lack of sufficiently specific university-level guidance. They also warned that too many overlapping guidelines could become difficult to interpret. This indicates that institutional preparedness depends not simply on regulatory volume but on operational clarity.

Infrastructure included more than computing capacity. Participants discussed access to high-quality models, licensed software, secure platforms, specialist databases, hardware, technical support and protected learning environments. At the University of Freiburg, some researchers paid personally for more capable tools because institutional access was not available. Subscription costs were also mentioned at Astana IT University.

The existence of national supercomputing capacity was not considered automatically relevant to lecturers or students. Participants were more concerned with whether usable, approved and affordable systems were available for actual teaching and research workflows.

Kazakh National Medical University participants connected infrastructure to faculty workload and professional development. They argued that continuous learning was difficult when academic staff faced heavy administrative and teaching responsibilities. Investment in software or equipment would have limited effect without time, training and organisational support.

Teacher training was among the strongest areas of agreement. Participants repeatedly argued that faculty development should precede or accompany student training because teachers were responsible for designing tasks, selecting tools, explaining limits and evaluating learning.

However, they were sceptical about one-off introductory seminars. Effective training needed to be practical, discipline-sensitive and connected to teachers' own courses. Relevant formats included workshops, applied cases, peer exchange, supervised experimentation, communities of practice and train-the-trainer arrangements.

Participants also emphasised the speed of change. Training material focused exclusively on current products would become obsolete quickly. More sustainable professional development should combine durable principles with frequently updated cases and tool demonstrations.

The evidence suggests that faculty development should cover four interconnected capacities: critical use of AI; educational and assessment design; disciplinary application; and ethical and institutional responsibility. A teacher may be competent in one area and still require support in another. Technical familiarity does not necessarily imply pedagogical competence, just as subject expertise does not ensure understanding of data governance or AI limitations.

4.9 Inclusion and accessibility

Inclusion was discussed most extensively in the IVI and Sapienza groups, although related issues appeared elsewhere through language, cost and unequal access.

Participants described **AI as potentially compensatory** for students with disabilities, specific learning disorders, special educational needs and neurodivergence. Relevant uses included simplifying or restructuring texts, generating concept maps, supporting reading and writing, translating material, producing alternative formats and personalising explanations.

A participant with experience as both an educator and university student argued that technological assistance was sometimes wrongly treated as an unfair shortcut rather than as a means of equal participation. This was linked to a broader concern that institutional culture might prevent students from using appropriate compensatory tools even when the educational objective did not depend on the restricted skill.

Psychology and education experts nevertheless warned that personalised support required careful evaluation. A generic model might not respond adequately to the needs of a neurodivergent student and could reproduce stereotypes or inappropriate assumptions. AI-generated support should therefore complement, not replace, professional knowledge of the learner. This addresses the need for adequate testing identified in the quantitative questionnaire (see: **3.6. Accessibility and inclusion**).

Language diversity was relevant across the project. AI-assisted translation could improve access to international literature and support students studying in multilingual environments. At the same time, participants in language-related fields warned that dependence on machine translation could reduce active language development. Curriculum design should therefore distinguish access-oriented translation from learning outcomes that require independent production.

Unequal access was discussed in terms of subscription costs, device quality, institutional licences and the difference between free and premium systems. Where better-performing or more secure tools require payment, students and teachers with fewer resources may receive lower-quality support or face greater privacy risks.

This creates a potential two-tier environment. Some users may have access to institutionally supported systems and verified databases, while others rely on free commercial tools. Institutional procurement and shared access are therefore part of inclusion, not merely technical administration.

Participants also recognised that accessibility benefits could coexist with new risks. Simplified content might become inaccurate. Translation could alter disciplinary meaning. Voice or biometric tools might collect sensitive information. Personalised systems could label users inappropriately or disclose disability-related data.

The qualitative implication is that inclusion should be treated as a design and evaluation criterion. AI is not inclusive merely because it offers adaptation. Tools and activities should be assessed in relation to accessibility, affordability, language coverage, data protection, user autonomy and the continued availability of human support.

4.10 Professional relevance and university–industry cooperation

Participants generally agreed that AI competence should be connected to real professional tasks. They questioned training that remained limited to generic chatbot use without reference to the conditions under which graduates would apply AI in employment.

Professional relevance differed markedly by sector. In medicine, students needed to evaluate diagnostic support, clinical data, uncertainty, patient safety and confidentiality (World Health Organization, 2021). In public health, relevant applications included literature analysis, epidemiological modelling and health-system planning. In psychology, professional relevance involved assessment validity, confidentiality, behavioural interpretation and the boundaries of automated support. In education, it included instructional design, accessibility, assessment, tutoring and learning analytics.

Technical and business-oriented participants referred to programming, product development, data analysis, patent searches, process automation and project planning. Humanities participants discussed research support, source analysis and the possibility of making complex cultural material more accessible, while also warning about fabricated references and loss of interpretative depth.

The focus-group evidence concerning **formal university–industry cooperation** was less extensive than the discussion of professional applications. Participants included external consultants, developers, public-sector experts and professionals using AI in applied settings, and their contributions demonstrated the value of external expertise. However, the corpus contains limited detailed information about existing internships, placement structures or systematic employer participation in curriculum design.

Where cooperation was discussed, it was generally framed as a way to keep curricula aligned with rapidly changing practice. External organisations could contribute real cases, tool access, datasets, professional mentors and information about emerging competence needs. Universities, however, would need to retain responsibility for educational quality, ethical safeguards and assessment.

The evidence suggests that placements should not be treated simply as opportunities to use advanced tools. Students should be required to document the professional problem, data source, limitations, verification process and role of human judgement. This would make internships part of competence development rather than technology exposure alone.

University–industry cooperation may also help institutions overcome resource limitations, but it introduces governance questions. Commercial access should not determine curriculum content uncritically, and students should not be required to transfer personal or institutional data to external systems without appropriate safeguards.

The qualitative material therefore supports structured cooperation based on shared educational objectives and clear responsibilities. It does not provide sufficient evidence to recommend a single partnership model across all institutions and disciplines.

4.11 Cross-group convergence and divergence

Common findings

The strongest convergence concerned the gap between widespread use and structured educational integration. Across national and disciplinary contexts, participants described AI as already present in teaching, learning, research and professional work. At the same time, they reported insufficient guidance, uneven competence, unclear assessment practices and reliance on individual experimentation.

A second common finding was that verification and critical judgement are central. Hallucinations, fabricated references, technically incorrect outputs and persuasive language appeared in almost every institutional context. Participants did not treat these as temporary technical inconveniences. They regarded them as educational reasons to strengthen disciplinary knowledge and explicit verification skills.

Assessment was another clear area of convergence. Conventional unsupervised assignments were considered increasingly unreliable as direct evidence of student competence. Participants supported greater transparency, process documentation, oral defence, supervised work and human review.

Human responsibility also received broad support. AI could assist with teaching materials, feedback, diagnostic support or preliminary analysis, but final academic and professional decisions should remain with appropriately qualified people.

Faculty development was consistently identified as necessary. The groups agreed that teachers required more than basic tool demonstrations. They needed practical support in task design, assessment, discipline-specific use, verification, privacy and inclusion.

National and institutional differences

The differences between countries should be interpreted cautiously because the focus groups were not designed as matched national samples. Nevertheless, some contextual distinctions were visible.

Central Asian participants more frequently described the absence of uniform institutional or ministerial guidance, bureaucratic obstacles to curriculum revision and limited practical impact from national AI infrastructure. They also emphasised the need to move from national strategic ambition to operational support within universities.

European participants referred more often to existing legal and competence frameworks, particularly data protection and digital-competence references. However, they did not describe these frameworks as sufficient. Their concern centred on fragmentation, excessive complexity and the lack of specific operational guidance for university teaching.

The difference is therefore not simply one between regulated and unregulated environments. In Kazakhstan and Uzbekistan, participants more often called for clearer foundational frameworks and institutional rules. In Italy and Germany, participants more often called for the translation of existing frameworks into usable, discipline-sensitive practice.

Institutional profile also shaped the findings. The technology-oriented AITU group discussed technical curricula, subscription costs, rapidly changing tools and the distinction between AI assistance and substitution. KazNMU participants focused on clinical responsibility, local data, foundational competence and curriculum structures in medical education. TSPU and YAU participants gave more attention to teacher readiness, student dependence, languages, psychology and assessment redesign. Freiburg participants emphasised scientific validity, intellectual property and secure infrastructure.

Disciplinary differences

Medicine and health-related discussions applied the common principles of verification and oversight to high-stakes professional decisions. Participants stressed that errors could affect patient safety and that recommendations developed from foreign or unrepresentative data might not suit the local context. Human responsibility therefore had legal and clinical as well as educational significance.

Education participants focused more on task design, teacher roles, adaptive support, student agency and the redesign of assessment. The principal question was how to use AI without allowing it to replace the thinking that educational activities were intended to develop.

Psychology-related participants emphasised empathy, confidentiality, validity and professional boundaries. They were concerned that apparently personalised output could conceal inappropriate generalisation and that sensitive data could be exposed through external platforms.

Language educators recognised translation as both an opportunity and a risk. It could support multilingual participation but also weaken the development of grammar, vocabulary and independent expression.

Technical participants were more likely to discuss code generation, prompt engineering, system design and the limits of general-purpose tools. However, they also emphasised ethical and governance content, suggesting that technical competence should not be separated from responsibility.

Contested issues

The groups did not reach complete agreement on the acceptable extent of AI use in student work. Some participants favoured relatively strict limitations, especially in early study stages or assignments designed to demonstrate individual competence. Others argued that prohibition was unrealistic and that transparent, traceable use should be accepted.

These positions are not necessarily incompatible. They reflect different assumptions about the learning outcome and the student's level of development. The evidence supports task-specific rules rather than a universal permission or prohibition.

There was also variation in views of automated detection. Most participants were sceptical, but some still regarded detection tools as potentially useful when combined with professional review. The disagreement concerns degree of reliance rather than whether detectors should have final authority.

Bias scenarios produced differing interpretations of whether responsibility lies primarily with developers, institutions or users. This indicates a need for more explicit education on the AI lifecycle and shared accountability.

Participants also differed in their confidence regarding controlled or closed AI environments. Some described them as substantially more reliable, while others emphasised that no environment removed the need for validation. EduCATIA should therefore avoid presenting any tool category as inherently trustworthy.

Insufficiently explored themes

Several topics require further investigation. The focus groups provide limited direct evidence from students, particularly regarding why they use AI, how they interpret institutional rules and what forms of disclosure they consider feasible.

The corpus also contains limited detailed discussion of AI's environmental costs, accessibility testing with disabled users, procurement procedures, intellectual-property ownership of generated materials and mechanisms for evaluating whether AI improves learning outcomes.

University–industry cooperation was discussed more as a project objective and professional need than as a description of existing practice. More information is required about current internships, employer partnerships, mentoring arrangements and access to professional datasets or platforms.

Public-health and biomedical applications were less extensively discussed than medicine, education and general generative-AI use. Their specific curriculum requirements should be developed through programme review and consultation with relevant specialists.

Finally, the sessions identified the need for continuous updating but did not define in detail who should hold institutional responsibility for monitoring changes, revising guidance and approving tools.

4.12 Implications for EduCATIA

The focus-group evidence confirms that EduCATIA should begin from a context of broad but fragmented AI adoption. Its principal contribution should not be limited to introducing additional tools or isolated technical subjects. It should help participating institutions convert current practices into explicit educational, professional and institutional capacities.

The qualitative findings support a common foundation in critical AI literacy, including problem formulation, prompting, verification, source evaluation, bias, privacy, transparency and human

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oversight. This foundation should be complemented by discipline-specific pathways that connect AI to authentic professional tasks and risks.

Assessment redesign should be treated as a central project priority. Programmes need clear rules on permitted use and disclosure, together with assessment methods that make student reasoning visible. Oral defence, staged work, practical application and supervised activities should be considered alongside conventional written assignments.

Faculty development should be practical, continuing and situated within particular disciplines. Teachers need support not only in using AI but in designing learning, evaluating outputs, protecting data, ensuring accessibility and transferring recognisable competences to students.

Institutional guidance should be brief enough to use, specific enough to guide real decisions and flexible enough to accommodate technological change. It should clarify responsibilities among academic staff, programme leaders, technical services, data-protection structures and institutional management.

The groups also reinforce the importance of inclusion. AI may improve accessibility, multilingual participation and support for students with fewer opportunities, but only where tools are affordable, evaluated with users and subject to suitable privacy and quality controls.

The overall qualitative conclusion is that educational maturity depends less on the number of AI tools available than on the quality of the pedagogical, ethical and institutional conditions surrounding their use. For EduCATIA, curriculum modernisation should therefore combine competence development, assessment reform, faculty capacity, governance, inclusive design and professionally relevant application.

5. Integrated interpretation of questionnaires and focus groups

The questionnaire and focus-group findings describe different dimensions of the same transition. The questionnaires establish the breadth of AI use, the distribution of reported competences and the visibility of institutional provision. The focus groups explain how these patterns are experienced in teaching, assessment and professional practice, and identify mechanisms that cannot be captured adequately through closed-response items.

The two components should not be treated as independent studies producing parallel conclusions. Their analytical value lies in the relationship between them. In several areas, the qualitative evidence confirms the direction of the questionnaire findings. In others, it qualifies apparently positive indicators by showing that reported use, training or competence transfer may remain informal, inconsistent or difficult for students to recognise. The focus groups also introduce concerns that were only partially addressed in the questionnaires, including curriculum rigidity, the risks associated with external platforms, local data relevance and the practical limits of automated detection.

5.1. Areas of convergence

The strongest convergence concerns the distinction between widespread adoption and limited educational institutionalisation. The questionnaires show that AI is already used by the large majority of students and teachers. The focus groups confirm that this use extends across teaching preparation, student assignments, research, translation, data analysis and professional tasks. At the same time, both sources indicate that formal curriculum integration,

explicit guidance and structured competence development remain less widespread than practical use.
A second area of convergence is the need for critical verification. Reliability was one of the principal concerns reported by teachers in the questionnaire. In the focus groups, this concern was expressed through concrete examples: fabricated references, inaccurate numerical information, unsuitable clinical recommendations, generated code containing errors and examination questions that did not correspond to the syllabus. The qualitative evidence therefore clarifies that verification is not a generic critical-thinking objective. It is an observable academic and professional competence that must be taught and assessed.

Assessment and academic integrity also show substantial convergence. Questionnaire respondents displayed more cautious attitudes towards AI use in assessment than towards its use in preparing materials or supporting assignments. Teachers expressed strong concern about dishonest practices and the possible weakening of critical thinking. The focus groups explain why assessment is especially sensitive: the quality of a submitted product can no longer be assumed to reflect independent student competence, and automated detection does not provide a sufficiently reliable solution.

Both evidence sources also support faculty development as a central condition of curriculum reform. Questionnaire participation in formal training was associated with more developed reported practices, while demand for further training remained high. Focus-group participants repeatedly argued that teachers must be prepared not only to operate AI tools, but also to design appropriate activities, supervise data use, verify outputs, redesign assessment and explain disciplinary limitations.

There was also broad convergence around human oversight. The questionnaires identified concern about reliability, fairness and professional responsibility. In the focus groups, participants consistently rejected the transfer of final authority to AI in grading, clinical decision-making or other consequential contexts. Human oversight emerged not as a general ethical slogan, but as a practical requirement for reviewing error, contextualising recommendations and retaining accountability.

The main areas of convergence are summarised below.

Theme	Questionnaire evidence	Focus-group evidence	Integrated interpretation
Extended use and limited institutionalisation	AI use is widespread among both students and teachers, while formal training, recognised guidance and curriculum visibility remain less extensive.	Participants described routine but largely individual experimentation, uneven rules and limited programme-level coordination.	The primary challenge is not initial adoption but the transition from spontaneous use to educational maturity.

Functional use and advanced competence	Frequent use coexists with low levels of self-reported advanced knowledge.	Participants distinguished between obtaining an output and understanding how to formulate, verify and apply it appropriately.	Operational familiarity should not be used as a proxy for AI competence.
Verification and critical thinking	Reliability and reduced critical thinking were major concerns, particularly among teachers.	Participants provided examples of hallucinations, invented references, incorrect code and persuasive but inaccurate responses.	Verification must become an explicit learning outcome embedded within disciplinary teaching.
Assessment and academic integrity	Acceptance of AI was lowest or most qualified in relation to assessment; concern about dishonest use was widespread.	Participants reported identical assignments, discrepancies between homework and supervised performance, and unreliable detector results.	Assessment reform should prioritise visible reasoning and transparent process rather than dependence on detection.
Privacy and governance	Only around half of respondents recognised institutional AI guidance.	Participants described unclear rules, unapproved external platforms, data leakage risks and uncertainty about institutional responsibility.	Guidance must move from general principles to operational rules at institutional, programme and module level.
Faculty development	Training coverage was incomplete, demand was high and trained teachers reported more developed practices.	Participants called for practical, continuing and discipline-specific development rather than isolated introductory seminars.	Faculty development is an implementation requirement, not a supplementary project activity.

Disciplinary applications	Academic areas showed different combinations of use, training, transfer and demand.	Participants linked AI to distinct professional tasks and risks in medicine, education, psychology, languages and technical fields.	A common competence foundation must be combined with discipline-specific pathways.
Inclusion	Accessibility-related use was already reported by more than half of students and teachers.	Participants described benefits for translation, neurodivergence and special educational needs, but also cost and privacy risks.	Inclusion should be designed and evaluated explicitly; the mere availability of AI does not guarantee accessibility.
Human responsibility	Respondents expressed caution regarding automated assessment and professional substitution.	Participants strongly supported human review and final authority in academic and professional decisions.	Human oversight should be embedded in learning outcomes, assessment and institutional procedures.

5.2. Complementary findings

The principal contribution of the focus groups is explanatory. They show how a quantitative indicator may conceal different educational realities.

The questionnaires, for example, demonstrate that teachers report transferring both general and discipline-specific AI competences more frequently than students report learning such competences from their professors. The qualitative evidence suggests several possible explanations. Teachers may demonstrate tools without defining explicit learning outcomes; students may use AI in a course without recognising the activity as competence development; or AI may be incorporated into task completion without structured practice, feedback or assessment.

The integrated interpretation is therefore not simply that competence transfer is insufficient. It is that transfer may be educationally invisible. Curriculum modernisation must make the intended competence recognisable to students and connect it to taught activities and assessment criteria.

The focus groups also add substance to the questionnaire distinction between use and knowledge. Quantitative self-assessment can identify that advanced knowledge is uncommon, but it cannot determine what respondents understand by advanced competence. Participants' accounts suggest that competence includes at least four connected capacities: problem formulation, appropriate prompting, output verification and context-sensitive decision-making. In professional fields, it also includes recognising when AI should not be used.

Similarly, the questionnaire findings establish widespread concern about critical thinking, but the focus groups identify the conditions under which AI may either weaken or support it. Critical thinking is weakened when AI replaces the central reasoning required by a task. It may be strengthened when students compare outputs, identify errors, challenge assumptions, evaluate sources or justify rejection of a recommendation. The relevant curricular question is therefore not whether AI is permitted in general, but what cognitive work the student remains required to perform.

The qualitative evidence also specifies the practical meaning of assessment redesign. Questionnaire responses indicate concern about academic integrity, but participants proposed concrete alternatives: oral defence, staged submissions, supervised tasks, portfolios, reflective commentaries and records of AI-supported processes. These methods make reasoning and responsibility visible without assuming that all AI use is misconduct. This complements the questionnaire-based recommendation that assessment should evaluate judgement, verification and disciplinary understanding rather than only the final product.

A further complementary contribution concerns institutional support. The questionnaire measures whether respondents perceive guidance to exist. The focus groups show that the effectiveness of guidance depends on its form. A university may have a policy while teachers remain uncertain about permitted uses, approved tools, disclosure requirements or data protection. Conversely, an institution may lack a comprehensive policy but have local practices within particular faculties. Institutional readiness should therefore be assessed through visibility, usability and consistency, not only through the formal existence of a document.

Disciplinary findings are also clarified by the qualitative evidence. Questionnaire comparisons indicate contrasting levels of use, training and demand among medicine, education and other fields. The focus groups explain that these differences correspond to distinct professional stakes. In medicine, verification concerns patient safety, local applicability, confidentiality and clinical accountability. In education, the central questions concern learning design, assessment and student agency. In psychology, they concern validity, empathy, sensitive data and the limits of automated support. These are not merely different examples of the same competence; they require different cases, safeguards and assessment methods.

5.3. Divergent or qualified findings

The integrated evidence also contains findings that should be interpreted with qualification rather than treated as direct confirmation.

The questionnaire results suggest relatively high levels of teacher-reported **field-specific competence transfer**. Focus-group accounts, however, often describe teaching practice as improvised and dependent on individual initiative. This does not necessarily constitute a contradiction. Teachers may regard informal explanation, demonstration or advice as competence transfer, while the qualitative discussions apply a stricter standard involving explicit outcomes, structured practice and assessment. The combined evidence therefore supports a distinction between reported transfer and curriculum-embedded transfer.

Institutional guidance presents a similar issue. Approximately half of questionnaire respondents recognised some form of guidance, yet focus-group participants frequently described rules as unclear, inconsistent or absent. This difference may arise because the survey captured broad awareness of any relevant provision, while the discussions focused on whether rules were sufficiently specific to resolve real cases. The integrated conclusion is that the principal problem is not only policy absence but limited operational clarity.

The evidence concerning **inclusion** also requires qualification. Questionnaire respondents reported substantial accessibility-related use, and focus-group participants identified considerable compensatory potential. However, the qualitative discussions warned that AI tools may generate inaccurate simplifications, perform unevenly across languages, expose sensitive information or create inequalities between users of free and paid services. High reported use should therefore not be interpreted as proof of effective or equitable inclusion.

Differences also appear in attitudes towards **student use**. Some questionnaire respondents accepted AI support in assignments, while teachers were more cautious about student use than about their own use. Focus-group participants likewise differed between those favouring relatively strict restrictions and those supporting transparent, declared use. These positions are best interpreted in relation to the purpose and level of the task. A single institutional rule allowing or prohibiting all AI-assisted work would not reflect the complexity of the evidence.

The qualitative evidence is also more cautious than some participant claims about **controlled systems**. A small number of contributors expressed strong confidence in platforms linked to selected databases. Other participants maintained that no environment removes the need for validation. The integrated interpretation should therefore avoid categorising closed or institutional systems as inherently accurate. They may reduce some risks while introducing others relating to configuration, data quality and inappropriate reliance.

Finally, **apparent national differences** must be treated carefully. Central Asian groups more frequently emphasised the lack of clear frameworks and barriers to curriculum revision, while European participants more frequently referred to existing regulation and competence frameworks. The groups were not matched national samples, and these differences may also reflect institution type, participant profile and discussion structure. They indicate contextual tendencies to be verified, not comparative rankings of national preparedness.

5.4. Issues emerging mainly from the focus groups

Several issues gained analytical prominence primarily through qualitative evidence.

The first is **curriculum rigidity**. Participants explained that formal approval procedures, departmental boundaries and fixed review cycles may prevent programmes from responding to technological changes. The questionnaires identify demand and gaps, but they do not capture whether universities possess mechanisms for revising content rapidly. The focus groups suggest that curriculum reform requires a stable competence framework combined with more flexible updating of examples, tools and teaching activities.

A second issue is the **distinction between public general-purpose tools and institutionally controlled environments**. Participants raised questions about subscription costs, access to specialist databases, enterprise licences and the need for approved platforms. This adds a procurement and infrastructure dimension to institutional preparedness.

A third issue is **local applicability**. Medical and public-health participants warned that models trained on external populations or healthcare systems may produce recommendations that are technically plausible but contextually unsuitable. This extends the concept of bias beyond demographic discrimination to include infrastructure, resource availability and national professional practice.

The focus groups also identified the risk of **invalid faculty use**. Questionnaire discussion of competence gaps focuses primarily on respondent knowledge and training, whereas the qualitative evidence illustrates how unverified use by teachers can affect students directly. Generated examination questions may fail to align with the syllabus, teaching materials may contain inaccurate information and automated feedback may acquire unjustified authority. Faculty AI literacy is therefore also a quality-assurance issue.

Another mainly qualitative issue is the **limitation of automated detection**. Participants questioned the reliability and fairness of identifying AI-generated work through current detection systems. This shifts the policy response away from surveillance and towards task design, transparency and human judgement.

The discussions also drew attention to **workload and time**. AI is frequently presented as a productivity tool, but participants noted that responsible use requires iterative prompting, source checking, review and correction. Faculty development and curriculum reform must account for the time needed to use AI properly rather than assuming that implementation will automatically reduce workload.

Finally, the focus groups raised questions of **distributed accountability**. Bias, data misuse and inappropriate automated decisions cannot be attributed exclusively to the developer, user or institution. Responsibility is shared across tool selection, data provision, system design, deployment and final decision-making. This issue requires clearer treatment in training and institutional governance.

5.5. Common educational and institutional priorities

The combined evidence supports a coherent set of priorities for EduCATIA.

The first priority is to define a **common foundation of critical and responsible AI literacy**. This should include basic system understanding, problem formulation, prompting, verification, source evaluation, bias, privacy, transparency and the limits of automation (Vuorikari et al., 2022; UNESCO, 2024a). These competences should be expressed as observable outcomes rather than as general awareness.

The second is to connect this common foundation to **discipline-specific professional pathways**. The content, examples and safeguards required in education, medicine, biomedical sciences, public health and psychology are not interchangeable. Each programme should identify authentic tasks in which students can practise AI-supported judgement without delegating professional responsibility.

The third priority is **assessment reform**. Programmes should specify when AI may be used, how its use must be declared and what evidence of independent competence remains necessary. Assessment methods should make reasoning visible and should combine AI-supported and, where appropriate, supervised or unaided performance.

The fourth is practical and continuing **faculty development**. Teachers need support in educational design, assessment, verification, data governance, accessibility and disciplinary application (Redecker, 2017; UNESCO, 2024b). Training should be linked to the modules they teach and supported by peer exchange, updated resources and local train-the-trainer capacity.

The fifth priority is **operational institutional governance**. Universities need concise and visible rules, approved or recommended tools, procedures for sensitive data, clear human-review rights and mechanisms for updating guidance. Policy should explain how responsible use is implemented, not only what is prohibited.

The sixth is **inclusive implementation**. AI-supported accessibility, translation and personalised assistance should be developed with users and evaluated for accuracy, affordability, language coverage, privacy and compatibility with assistive technologies.

The seventh is the **preservation of human responsibility**. Students, teachers and professionals should be trained to identify when an AI output is unsuitable, justify the final decision and remain accountable for its consequences. This principle should apply across curriculum design, assessment, institutional services and professional practice.

Taken together, the evidence indicates that EduCATIA should not measure progress principally through the frequency of AI use, the number of tools introduced or the number of isolated training events. Progress should be demonstrated through explicit and assessable competences, valid assessment, trained faculty, usable governance, inclusive provision and the responsible application of AI within authentic disciplinary contexts. The central project task is therefore to move from broad adoption to coherent educational and institutional maturity.

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3. Partner Site: AITU (Astana IT University)

- EduCATIA Project - AITU Partner. (2026). *Educatia focus group AITU* [Transcript/Document]. Google Drive. https://docs.google.com/document/d/18WIN75-P-0s5ANMmeAe8nexBJiGuVwfi/edit?usp=drivesdk
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5. Partner Site: KazNMU (Kazakh National Medical University)

- EduCATIA Project - KazNMU Partner. (2026). *Educatia focus group KazNMU* [Audio file]. Google Drive. https://drive.google.com/file/d/1GJWOU03ITUOSQO4JQZhwG4toug9qhF3W/view?usp=drivesdk
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6. Partner Site: Sapienza (Sapienza Università di Roma)

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7. Partner Site: TSPU (Tashkent State Pedagogical University)

A. General Documents & Executive Report

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C. Questionnaires and Individual Surveys (Russian Version)

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9. Partner Site: YAU (Yeoju Technical Institute / YAU)

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B. Questionnaires and Individual Surveys (English Version)

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C. Questionnaires and Individual Surveys (Russian Version)

- EduCATIA Project - YAU Partner. (2026). *EduCATIA Focus Group Protocol - YAU Questionnaire_Batirova G* [Questionnaire/Protocol]. Google Drive. https://docs.google.com/document/d/1KHRJlybCoS_t0_G--GNSgVT32_u1U3bi/edit?usp=drivesdk
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Introduction to the Degree Analysis

Selection and relevance of the programmes

The degree analysis forms the programme-level component of the EduCATIA investigation into AI-related educational gaps in Kazakhstan and Uzbekistan. Its purpose is to move from general evidence about AI use and perceived needs to the specific curricula, learning outcomes, modules, professional responsibilities and assessment practices through which sustainable competence development must occur.

The Grant Agreement places particular emphasis on Education and Health Sciences. These areas remain central to the analysis because AI has immediate implications for teaching, learning, assessment, patient safety, pharmaceutical practice, epidemiological decision-making and public-health governance. Accordingly, the selected programmes include Philology and Language Teaching in Uzbekistan and Pharmacy and Medical and Preventive Medicine in Kazakhstan.

The final selection was not determined by disciplinary classification alone. Partner universities and the relevant ministries asked the project to consider programmes that were of particular strategic value to their institutions and had a concrete priority for modernisation within EduCATIA. This institutional demand led to the inclusion of Psychology and IT Entrepreneurship beyond the narrowly required Education and Health Sciences focus.

Psychology was prioritised because Uzbekistan has recently established a new legal framework for psychological assistance, while universities face significant student mental-health needs and limited availability of organised support. Digital and AI-supported psychological services raise particularly sensitive issues of confidentiality, validity, bias, informed consent, crisis escalation and professional responsibility. Modernising the Psychology degree therefore connects curriculum development with professional regulation, student wellbeing and the development of a qualified workforce capable of using digital systems without delegating psychological judgement.

IT Entrepreneurship was prioritised by Astana IT University because it is strategically important for innovation, digital transformation and the development of AI-enabled products and enterprises. The programme already contains substantial technical and managerial foundations. Its modernisation offers an opportunity to demonstrate that responsible AI education is necessary even in programmes where machine learning and data mining are already taught. Technical competence must be complemented by critical evaluation, governance, human oversight, data protection, accessibility, responsible innovation and valid assessment.

The inclusion of these programmes reflects the partnership-based character of EduCATIA. The purpose of the project is not to impose an externally predetermined list of degrees, but to combine the objectives of the Grant Agreement with the development priorities identified by participating institutions and public authorities. This approach increases institutional ownership and makes it more likely that the findings will lead to implemented curriculum reforms.

Analytical approach

Each programme was analysed on the basis of the available official or institutional documentation. The analysis examined programme learning outcomes, module structures, professional profiles, practice components, assessment approaches and relevant digital or data-related provision. It distinguished explicit AI content from general ICT, statistics, automation or innovation. Existing digital foundations were treated as potential anchors for modernisation, but they were not automatically classified as AI education.

The curriculum findings were then compared with the questionnaire and focus-group evidence. This triangulation made it possible to distinguish gaps documented in the curriculum from needs supported by multiple sources. It also helped identify where an apparent absence may require further verification because detailed syllabi, assessment briefs, current teaching practices, staff profiles or institutional policies were unavailable.

Recommendations are therefore provisional directions for curriculum design, not pre-approved amendments. They identify competence needs and plausible curricular locations while leaving decisions about credits, hours, module ownership, named tools and implementation schedules to the responsible institutions.

Integration of DigComp 3.0

A DigComp 3.0 analysis was added to provide an extensive and consecutive examination of the programmes against an EU framework for digital and AI competence development. The framework connects the empirical findings to 21 defined competence areas covering information evaluation and management, communication and collaboration, content creation, safety and responsible use, and problem solving.

The analysis estimates that the modal student currently operates at Basic to Intermediate functional proficiency, whereas a Bachelor's graduate should generally reach Advanced proficiency. The largest gaps concern critical evaluation of AI information, privacy and data protection, integration of AI-generated content into disciplinary work, responsible professional application, environmental awareness and autonomous lifelong learning.

The accompanying learning-outcome specification translates these gaps into observable knowledge, skills, attitudes and evidence of attainment. It therefore provides more than a retrospective diagnosis. It offers a common design framework that programme teams can use to formulate graduate outcomes, develop teaching activities and verify achievement through assessment.

DigComp should not replace professional standards or discipline-specific requirements. Its role is to provide a coherent common sequence. The same competence—for example, verification—must then be contextualised differently in language teaching, psychological assessment, pharmacovigilance, public-health surveillance or AI-enabled entrepreneurship.

Recommendations for the Modernisation of the Degree Programme in Psychology in Uzbekistan

Analysis of the Bachelor's Degree 60310300 – Psychology and of Law No. ZRU-989 "On the Provision of Psychological Assistance to the Population", in the light of the EduCATIA needs analysis and of the European legal, deontological and technological framework

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1. Introduction and conceptual framework

This document is produced within the Erasmus+ Capacity Building in Higher Education project EduCATIA – Advanced Training in Artificial Intelligence Technologies for Kazakhstan and Uzbekistan. Among the four academic areas addressed by the project (education and pedagogy; medicine; biomedical sciences and public health; psychological sciences and cognitive research), this report focuses on the psychological sciences and delivers the structured review of the degree programme selected for modernisation announced in the EduCATIA needs analysis (Perone, Giordano & Martínez de Carnero, 2026): it moves from the level of broad academic areas to the level of the actual programme, its modules, learning outcomes and professional requirements.

The analysis is built on the systematic comparison of three sources: (i) the current national Qualification Requirements for the Bachelor's degree 60310300 – Psychology of the Republic of Uzbekistan (Order No. 218 of the Ministry of Higher Education, Science and Innovation, 25 June 2024); (ii) Law of the Republic of Uzbekistan No. ZRU-989 "On the Provision of Psychological Assistance to the Population" (5 November 2024, effective February 2025), which for the first time establishes the profession of psychologist in Uzbekistan; and (iii) the empirical evidence produced by the EduCATIA questionnaires administered to students and teachers of the partner universities, complemented by recent multi-screening studies on the mental health of Uzbek university students (Akharov & Khan, 2024; 2025).

The conceptual framework is comparative. The Uzbek degree and legal framework are read against the Italian and European reference systems: the Italian degree structure in psychological sciences and techniques (L-24) and psychology (LM-51); the Italian law establishing the profession of psychologist (Law No. 56 of 18 February 1989) and its evolution into a recognised health profession (Law No. 3/2018); the European deontological and certification frameworks (EFPA – EuroPsy); the European Union regulatory framework on artificial intelligence (Regulation (EU) 2024/1689, the "AI Act") and the European Commission's Ethical Guidelines on the Use of Artificial Intelligence and Data in Teaching and Learning (2022); and the EU policy framework on mental health (European Commission Communication "A comprehensive approach to mental health", COM(2023) 298). The comparison is deliberately asymmetric in time: the Italian profession was legally established in 1989 and has accumulated thirty-five years of regulatory, deontological and educational refinement, whereas the Uzbek profession was legally established in 2024. This asymmetry is not read as a deficit but as an opportunity: Uzbekistan can incorporate directly, at the foundation stage of its professional system, the lessons that European systems learned incrementally – including those concerning digitalisation and artificial intelligence.

The document is organised as follows. Section 2 analyses the current degree and compares it with the Italian degree system, in terms of subjects studied and credit recognition. Section 3 analyses the legal and deontological framework created by Law ZRU-989 and compares it with the Italian and European frameworks, identifying the structural gaps of the new law. Section 4 documents the mental health needs of the nation. Section 5 presents the digital revolution in psychology and the reasons why digitalisation is an opportunity for Uzbekistan. Section 6 addresses artificial intelligence in psychology and in psychology education, including the risks and the lawful and unlawful uses under the EU AI Act, compared with the Uzbek framework. Section 7 consolidates the findings in a gap matrix. Section 8 formulates the recommendations for the modernisation of the degree.

2. The current Bachelor's degree in Psychology in Uzbekistan (60310300)

2.1. Structure of the programme

The field of study 60310300 – Psychology belongs to the social and behavioural sciences and is delivered in full-time, evening and part-time forms, organised on a credit-module system, with a standard full-time duration of four years and a total workload of 240 credits (7,200 hours). The programme is structured as follows: 164 credits of compulsory courses, 40 credits of elective courses (with a Psychology/Pedagogy classification), 22 credits of qualification internship (semesters 4, 6 and 8) and 8 credits for the Final State Attestation.

The compulsory catalogue combines a general-education block (Higher Mathematics; Recent History of Uzbekistan; Philosophy; Uzbek/Russian Language; Foreign Language; Religious Studies; Digital and Information Technologies; Physical Education) with a strong classical psychology core: General Psychology (24 credits across four semesters), Experimental Psychology (16), Developmental and Differential Psychology (10), General Psychodiagnostics (10), Social Psychology (12), Methods and Technologies of Psychological Data Processing (6), Psychological Counselling and Psychocorrection (6), Fundamentals of Psychological Training (4), Pedagogical Psychology and Methods of Teaching Psychology (6), Clinical Psychology (6), Legal Psychology (4), Family Psychology (4), Labour and Engineering Psychology (4), History of Psychology (6), together with General Pedagogy (6) and Introduction to the Speciality (6).

The Qualification Requirements define six types of professional activity (scientific research; organisational and managerial; spiritual and awareness-raising; project-based; pedagogical; provision of various services) at level 6 of the National Qualifications Framework, and an extensive list of professional tasks including psychodiagnostics, psychological counselling, psychocorrection, psychoprophylaxis and psychological awareness-raising in educational institutions, enterprises, rehabilitation centres, sports teams, military and law-enforcement structures and private psychological service centres.

Observations

- The programme is solid and coherent in its classical foundations: the sequence General Psychology, Experimental Psychology, Psychodiagnostics, Counselling/Psychocorrection follows the canonical architecture of psychological training, and the weight given to psychodiagnostics (10 credits plus 6 credits of data-processing methods) is a strength to be preserved and valorised.
- Digital content is limited to one generic course, "Digital and Information Technologies" (6 credits, semester 2), which is not psychology-specific. The catalogue contains no course on digital psychology, tele-psychology, digital psychological assessment, or artificial intelligence applied to psychology.
- Although Law ZRU-989 explicitly permits the provision of psychological assistance "through the use of information and communication technologies" (Article 6), the

degree does not train graduates in the methodologies, ethics and technical standards of remotely delivered psychological assistance.

- The professional tasks list anticipates work in psychological services of educational institutions, but the internship structure (introductory, production, pre-graduation) does not currently guarantee a supervised placement within a functioning psychological service unit – which, as Section 4 shows, barely exist in the higher education sector.
- No course addresses the deontological and legal framework of the newly established profession (Law ZRU-989, code of ethics of the public associations of psychologists, confidentiality regime of Article 17), although Legal Psychology (4 credits) offers a natural anchor point.

Structure of the Bachelor's Degree in Psychology in Uzbekistan

Programme 60310300 – Psychology

The undergraduate programme in Psychology in Uzbekistan is a four-year (8-semester) full-time degree worth 240 ECTS credits (≈ 60 ECTS per academic year).

DURATION
4 years
(8 semesters)

TOTAL WORKLOAD
240 ECTS credits
(≈ 60 ECTS per year)

QUALIFICATION
Bachelor of Psychology

FOCUS
Formation of general, professional and practical competencies to work in psychological, educational, social and organisational settings.

CURRICULUM STRUCTURE ACROSS 8 SEMESTERS

Academic Year	Semesters	Typical Credit Load (ECTS)	Main Focus
YEAR 1 Foundations of Psychology and Social Sciences	Semester 1 Semester 2	60	• General Psychology • Social Sciences • Philosophy and Logic • Foreign Language • Information Technologies • Academic Writing • Physical Education
YEAR 2 Core Psychological Disciplines	Semester 3 Semester 4	60	• Developmental Psychology • Personality Psychology • General and Social Psychology • Psychometrics • Physiological Bases of Psychological Activity • Research Methods in Psychology
YEAR 3 Applied Areas and Professional Preparation	Semester 5 Semester 6	60	• Educational Psychology • Counselling Psychology • Clinical Psychology (basics) • Organisational Psychology • Psychodiagnostics • Statistics and Data Analysis • Elective Modules
YEAR 4 Specialisation, Practice and Graduation	Semester 7 Semester 8	60	• Advanced Electives • Practical Training / Internship • Research Project • Bachelor's Thesis • Professional Ethics

PROGRAMME FEATURES

- Combines **theoretical knowledge** with **practical training**.
- Includes **internships and field practice** in the final year.
- Promotes **research skills** and **evidence-based practice**.
- Prepares graduates for **diverse professional contexts**.

LEARNING OUTCOMES

Graduates are expected to be able to:

- Understand major psychological theories and concepts.
- Use psychological assessment methods appropriately.
- Design and conduct psychological research.
- Apply psychological knowledge to real-life professional situations.
- Communicate effectively and act ethically in professional settings.

PROFESSIONAL PATHS

Graduates can work in:

- Education (schools, universities)
- Healthcare and mental health services
- Human resources and organisational settings
- Social services and NGOs
- Research institutes and public institutions

OVERALL AIM
To develop competent, ethically responsible and socially oriented psychologists who can contribute to the well-being of individuals, organisations and society.

Figure 9. Structure of the Bachelor's Degree in Psychology in Uzbekistan

2.2. Comparison with the Italian degree system in psychology

In Italy, access to the profession of psychologist requires a five-year university pathway: a three-year Bachelor's degree in Psychological Sciences and Techniques (class L-24, 180 ECTS) followed by a two-year Master's degree in Psychology (class LM-51, 120 ECTS). Since Law No. 163/2021 the Master's degree is directly qualifying (laurea abilitante): it incorporates a supervised practical-evaluative traineeship and a final practical-evaluative examination, replacing the former post-degree State examination. The L-24 class requires coverage of all the scientific-disciplinary sectors of psychology (general psychology, psychobiology, psychometrics, developmental psychology, social psychology, work and organisational psychology, dynamic psychology, clinical psychology), together with foundations in biology, philosophy, sociology, statistics and informatics.

The comparison in terms of subjects studied and credit recognition can be summarised as follows.

Dimension	**Uzbekistan – 60310300 (Bachelor)**	**Italy – L-24 + LM-51**
Duration and volume	4 years, 240 credits (7,200 h)	3 + 2 years, 180 + 120 ECTS (300 ECTS total)
Level required to practise	Bachelor's degree gives access to the profession (Law ZRU-989, Art. 13)	Master's degree (LM-51) required; qualifying since Law 163/2021
Classical core	Strong: general, experimental, developmental, social, clinical, psychodiagnostics	Strong and sectorised (M-PSI/01–08), with compulsory psychometrics and psychobiology
Supervised practice	22 credits of internship; no guaranteed placement in a psychological service unit	Structured practical-evaluative traineeship integrated in the qualifying degree, under supervision of a licensed psychologist
Deontology and professional law	Absent as a dedicated subject	Compulsory: the Codice Deontologico (CDPI, current text) is binding on all registered psychologists and examined within the qualifying pathway
Digital psychology / tele-psychology	Absent	Present; CDPI Art. 1 extends all deontological rules to distance practice; tele-psychology normalised after COVID-19
Artificial intelligence	Absent	Emerging: AI, big data and digital tools modules appear in LM-51 curricula and continuing education (see Section 6.5)

Continuing education	Not regulated (see Section 3.4)	Compulsory ECM (continuing medical education) credits, since psychology is a health profession (Law 3/2018)

In terms of credit recognition, the Uzbek Bachelor's degree (240 credits) is quantitatively larger than the Italian L-24 (180 ECTS) but functionally corresponds to the pre-professional level of the Italian system: in the EU, and under the EFPA EuroPsy standard, independent professional practice as a psychologist requires the equivalent of five years of university education in psychology (300 ECTS) plus one year of supervised practice. The Uzbek system, by contrast, grants access to professional activity with the four-year Bachelor's degree – and, as discussed in Section 3, even with a one-year retraining course for graduates of other fields. This structural difference is the single most important element to govern in the modernisation process: the degree must be valorised as the full and reliable pathway into the profession, progressively closing the shorter routes or confining them to narrowly defined functions.

3. The legal and deontological framework

3.1. Law ZRU-989: the establishment of the profession of psychologist in Uzbekistan

Law No. ZRU-989 "On the Provision of Psychological Assistance to the Population", adopted by the Legislative Chamber on 23 July 2024, approved by the Senate on 20 September 2024, signed on 5 November 2024 and effective from February 2025, is a foundational act: for the first time in the history of the Republic of Uzbekistan it defines the profession of psychologist, its duties and responsibilities, and establishes a legal framework for its recognition. Its main building blocks are:

- Definitions and principles (Articles 3–4): the psychologist is defined as the natural person entitled to provide psychological assistance; the principles are legality, voluntariness, social protection, respect for human rights, professionalism and confidentiality.
- Types and forms of assistance (Article 6): psychological prevention, examination, rehabilitation, correction, counselling and training. Assistance may be provided in person or through information and communication technologies, individually or in groups – an explicit legal opening to digital psychology.
- Standards of provision (Article 7): to be developed and approved by the Ministry of Health, including permitted methods and means, qualification requirements for psychologists, and information duties. The law therefore distinguishes between authorised and non-authorised psychological methodologies.
- Free assistance guaranteed by the State (Article 9) for vulnerable categories, including learners in state pre-school and general secondary institutions, victims of violence and trafficking, low-income families and persons with disabilities.
- Psychological assistance in educational organisations (Article 10): in pre-school, general secondary, secondary specialised and professional educational organisations, psychological assistance must be organised through psychological services, in cooperation with teachers, heads and legal representatives.

- Public associations of psychologists (Article 12): non-governmental bodies with at least 300 members which approve the code of ethics, issue qualification certificates for private practice, keep public registers and exercise disciplinary control.
- Access to the profession (Article 13): analysed in detail in Section 3.4.
- Rights, obligations and refusal (Articles 14–16): humane treatment, information duties, contract requirements, prohibition of non-permitted methods, obligation to refuse when the psychologist lacks the necessary knowledge and skills in the area requested.
- Professional secrecy (Article 17): information acquired in the course of psychological assistance is the psychologist's professional secret and is equated to medical confidentiality; anonymised use is allowed for quality improvement and for training qualified personnel – a clause of direct relevance for university teaching and research.
- Title protection (Article 13, final paragraph, and Article 20): persons not entitled to provide psychological assistance are prohibited from using the word "psychologist" or similar words; administrative liability is introduced into the Code on Administrative Liability.

The law is complemented by Law No. ZRU-690 "On Mental Health Services" (12 May 2021) and by the Presidential Decree "On Measures to Fundamentally Improve the Public Mental Health Service" (June 2023), which together aim to integrate mental health into primary care and to increase the number of qualified specialists.

3.2. The Italian comparison: thirty-five years of professional regulation

Italy established the profession of psychologist with Law No. 56 of 18 February 1989, which created the professional order (Ordine degli Psicologi), the professional register, the State examination and the protection of the professional title. The Italian trajectory since 1989 offers three lessons of direct relevance for Uzbekistan. First, the definition of the acts reserved to the psychologist (Article 1 of Law 56/1989: the use of cognitive and intervention tools for prevention, diagnosis, habilitation-rehabilitation and support activities in the psychological field) was progressively clarified through deontological jurisprudence, showing that title protection is effective only if coupled with a clear definition of reserved professional acts. Second, with Law No. 3/2018 the psychologist was recognised as a health profession, with the consequent application of health-sector rules on continuing education (ECM credits), advertising, and integration into the national health service. In Uzbekistan psychologists are not yet recognised as health professionals; nevertheless Article 17 of Law ZRU-989 already equates psychological confidentiality to medical confidentiality, and Article 7 assigns the standards of provision to the Ministry of Health – two signals that the Uzbek system is converging towards the health-profession model and should be supported in that direction. Third, the Italian deontological code demonstrates that the code of ethics is a living instrument that evolves with technology: its current text (CDPI) expressly extends all its rules to services provided at a distance, via Internet or any other electronic or telematic means (Article 1), and even provides for a permanent Observatory collecting deontological case law for the periodic revision of the Code (Article 41); Article 12 of Law ZRU-989 wisely assigns the code to the public associations of psychologists, but those associations are newly formed and will need capacity building – an area where EU–Uzbekistan academic cooperation can contribute directly.

At the European level, the EFPA EuroPsy certificate sets the reference benchmark for the profession: at least five years of academic education in psychology and at least one year of supervised practice, together with adherence to the EFPA Meta-Code of Ethics and a commitment to continuing professional development. EuroPsy provides a ready-made template against which both the Uzbek degree and the Uzbek retraining routes can be benchmarked.

A methodological caveat must accompany the European benchmark. There is no single EU law establishing uniform access requirements or a common professional register for psychologists: psychology is not among the professions covered by automatic recognition under Article 21 of Directive 2005/36/EC on the recognition of professional qualifications, and falls instead under the general recognition system, in which host Member States compare qualifications case by case. The European reference level used in this report therefore combines binding EU rules – essentially those concerning data protection and artificial intelligence – with non-binding professional standards (EuroPsy and the EFPA ethical frameworks) that carry authority but not legal force. The practical consequence for the recommendations of Section 8 is that the direction proposed is not the mechanical transplantation of the Italian system: Uzbekistan should develop its own model, progressively introducing a unified public-interest governance layer, clearer competence boundaries, stronger supervised practice, continuing professional development and specific safeguards for digital and AI-supported activity (Gaps 4–6 and Recommendations R11–R13 below).

3.3. Deontological comparison: the Italian Code and Law ZRU-989 article by article

The current Codice Deontologico delle Psicologhe e degli Psicologi Italiani (CDPI), binding on all registered psychologists pursuant to Law 56/1989 and enforced through the disciplinary procedures of its Article 2, provides a precise benchmark against which the deontological layer of the Uzbek system can be assessed. The comparison shows convergence in principles and divergence in maturity, specification and enforcement. The following correspondences and gaps are the most consequential for the degree modernisation:

Deontological dimension	Italy – CDPI (current text)	Uzbekistan – Law ZRU-989 and emerging codes
Scope, including digital practice	Art. 1: the Code applies to all registered psychologists and expressly to services provided at a distance, via Internet or any other electronic/telematic means	Art. 6 permits ICT-mediated assistance, but no deontological rules specific to distance practice yet exist
Competence and continuing education	Art. 5: duty to maintain adequate preparation and professional updating; violation of the continuing-education obligation is a disciplinary offence; use only of instruments for which adequate	Art. 16 obliges refusal outside one's competence; Art. 7 reserves permitted methods to Ministry of Health standards;

	competence (and, where needed, formal authorisation) has been acquired	but no CPD obligation exists (Gap 2, Section 3.4)
Validity of data and instruments	Art. 7: duty to assess validity, reliability and accuracy of data, information and sources, exposing alternative interpretations and limits; Art. 25: no improper use of diagnostic instruments; communication of results adapted to protect the person	Implicit in the authorised-methodologies regime (Art. 7); no explicit duty on validity assessment or on the communication of results
Professional secrecy	Arts. 11–17: strict professional secrecy; limited derogations (referto/denuncia, grave danger to life or psychophysical health); anonymity in scientific communications; documents protected and retained for at least five years	Art. 17: professional secret equated to medical confidentiality; derogations for judicial requests and anonymised use for quality and training; no retention rules yet
Informed consent	Arts. 24, 31: written/documented informed consent as an exclusive responsibility of the psychologist; assent of minors according to age and maturity	Art. 8: consent of the person or legal representative; exceptions for minors under fourteen in cases of violence or emergencies; Art. 11: written consent for research
Title protection and unauthorised practice	Art. 8 CDPI: duty to counter unauthorised practice and report cases to the Order; Art. 21: teaching professional methods, techniques and instruments to persons outside the profession is a grave deontological violation	Art. 13, final paragraph: prohibition of the word “psychologist” for non-entitled persons; administrative liability (Art. 20); but the retraining route itself transfers professional techniques to non-psychology graduates in one year
Enforcement body	A single public professional Order with registers, disciplinary procedures (Art. 2 CDPI; Art. 26 L. 56/1989) and a permanent Observatory on deontological case law (Art. 41)	Plural private associations (Art. 12), each with its own code, register and disciplinary powers – risk of fragmentation and forum shopping among associations

Three conclusions follow. First, the Italian Code demonstrates that digital practice does not require a separate deontology: Article 1 CDPI simply extends the entire Code to services delivered at a distance, so that competence, consent, secrecy and validity duties apply identically online – the cleanest model for the standards that the Uzbek Ministry of Health must draft under Article 7 of ZRU-989. Second, Article 5 CDPI shows how the missing CPD layer (Gap 2) is closed in a mature system: continuing education is not an aspiration but a deontological duty whose violation is disciplinarily sanctioned – the regulatory recommendation of R7 should propose exactly this construction. Third, Article 21 CDPI – which qualifies as a grave violation the teaching of professional methods and instruments to persons outside the profession, with an aggravation where the teaching prepares unauthorised practice – throws the sharpest comparative light on the Uzbek retraining route: what the Italian deontological system prohibits as a matter of professional integrity, the Uzbek system currently institutionalises as an access route. This is not an argument against the retrained practitioners themselves, but a further argument for R8: the valorisation of the degree as the full pathway, and the confinement of the retraining route within narrowly defined, psychodiagnostics-free functions until bridging to the degree is completed. All of these divergences have direct curricular implications: the degree is the natural place where a unified professional culture, competence boundaries and digital deontology can be built before fragmentation consolidates, and the modernised module proposed in R4 should adopt the CDPI, alongside the EFPA Meta-Code, as its comparative reference text.

3.4. The structural gaps of Law ZRU-989

Gap 1. The one-year retraining route into the profession

Article 13 establishes a dual access regime. Persons holding higher education in psychology are entitled to provide psychological assistance. Persons holding higher education in any other field become entitled, after completing a retraining course in the speciality of psychology, to provide the corresponding types of psychological assistance in state bodies, including educational organisations; for private practice they additionally need the qualification certificate of a public association, and their activity is limited to psychological counselling and psychological training.

The retraining course, delivered by the Republican Psychological Centre – the national body under the competent state authority responsible for retraining and for the accreditation of psychological methodologies – lasts one year, covering approximately 700 hours of in-person lessons on the psychological profession, personality correction, intellectual, cognitive and emotional training, the major schools of psychotherapy, child, adolescent and family psychology, psychological counselling, coaching techniques, methods for organising and conducting psychological training sessions, and psychological supervision. Two features of this programme are critical. First, it omits the fundamental pillars of psychological assessment: it contains no substantial content on the administration of psychological testing and psychodiagnostics in the area of mental health assessment. Second, it compresses into one year (700 hours) a professional preparation that the degree develops over four years (7,200 hours) and that the European benchmark sets at five years plus supervised practice. The result is a profession that legally integrates, side by side, professionals with radically heterogeneous preparation – four years of dedicated study versus one year of retraining – creating substantial competence gaps within the profession. In practical terms, the retraining route operates as a large-scale regularisation (a “condono”) of pre-existing practitioners.

It must be acknowledged that the limitation of privately practising retrained professionals to counselling and training only (Article 13, paragraph 4) shows that the legislator is aware of the competence differential: psychological examination, correction and rehabilitation in private practice remain reserved to psychology graduates. However, in state bodies – including the educational organisations where Article 10 mandates psychological services – retrained professionals may provide "the corresponding types" of assistance, which leaves the most sensitive settings (schools, where minors are assessed) exposed to the weakest preparation, precisely where psychodiagnostic competence is most needed and least covered by the retraining curriculum.

Gap 2. The absence of continuous professional development

Law ZRU-989 clearly defines initial training and accreditation, and clearly distinguishes authorised from non-authorised methodologies (Article 7), but contains no provision on the continuous professional development of psychologists after authorisation. In the EU, continuing education is a structural requirement of the profession – in Italy, as a health profession, psychologists accrue compulsory ECM credits; under EuroPsy, the certificate must be renewed on the basis of documented practice and continuing professional development – precisely to prevent the use of outdated methodologies and techniques not aligned with the current state of psychological science. The absence of a CPD framework in Uzbekistan exposes the newly authorised profession, and especially its retrained component, to progressive scientific obsolescence. A digitalised, replicable, low-cost system of continuous training is the natural remedy, and higher education institutions are its natural providers (see Recommendations R7 and R8).

Gap 3. Health-profession status and the tertiary education blind spot

Two further gaps complete the picture. First, as noted, psychologists in Uzbekistan are not recognised as health professionals, which weakens the integration of psychological assistance into the health system that Law ZRU-690/2021 and the 2023 Presidential Decree pursue. Second, Article 10 mandates psychological services in pre-school, general secondary, secondary specialised and professional educational organisations – but not in higher education institutions. The permeability of psychologists into the tertiary level of education is currently missing from the law, exactly where, as Section 4 documents, the measured need is most acute. The degree modernisation exercise and the associated policy recommendations should therefore promote the extension of the Article 10 model to HEIs.

Gap 4. Fragmented professional governance

Article 12 assigns major regulatory functions to the public associations of psychologists with at least 300 members: each association approves its own code of ethics, issues the qualification certificates required for private practice, maintains its own register and exercises disciplinary control over its members. Because each psychologist may belong to only one association, practitioners performing substantially identical activities can be governed by different ethical interpretations, certification criteria and disciplinary practices. Section 3.3 identified this as a risk of fragmentation and forum shopping; it must be recognised as a structural gap in its own right, because it undermines the premise on which public protection rests – that individuals receiving the same type of psychological service benefit from the same minimum standards of competence, ethics, accountability and legal protection, regardless of the practitioner's association. The Italian counter-model (a statutory Order, a single binding code, disciplinary procedures under public law) shows one solution; Recommendation R11 proposes a lighter, phased alternative that does not require abolishing the existing associations.

Gap 5. Undifferentiated scope of practice without specialist pathways

The Qualification Requirements prepare graduates for work in schools, private centres, enterprises, rehabilitation services, sports, military and law-enforcement settings, and expect them to conduct psychological examinations, formulate diagnoses, provide counselling and psychocorrection, deliver emergency assistance and organise paid services. The problem is not the breadth of the profession but the absence of differentiation: the framework does not distinguish general psychological practice from psychodiagnostic assessment, clinical and rehabilitation work, emergency and trauma intervention, work with minors, organisational, forensic and military practice, psychotherapy, or professional supervision. Two absences are especially consequential. Psychotherapy is nowhere distinguished from general counselling and psychocorrection – there is no protected title, no dedicated postgraduate route and no way for a service user to know which form of intervention they are receiving. And professional supervision – on which the internship reform of R5 and the CPD system of R7 both depend – is not recognised as an advanced function with its own competence requirements. The bachelor's degree may reasonably ground entry into general practice; it cannot, by itself, authorise independent work across every setting and intervention listed. Recommendation R12 addresses this through a tiered, activity-based framework.

Gap 6. Consent, minors, confidentiality and records: principles without operational rules

Law ZRU-989 states the right principles – consent of the person or their legal representative (Article 8, with exceptions for children under fourteen in situations of violence or emergency), professional secrecy equated to medical confidentiality (Article 17) – but does not translate them into operational rules. Three pressure points stand out. First, Article 10 obliges psychologists in educational organisations to provide legal representatives with information on learners' psychological state and needs: read without safeguards, this risks turning school psychologists into automatic reporting channels to parents and institutional managers, and deterring precisely the minors – for example those seeking help about violence, abuse or family conflict – whom the service exists to protect. Second, Article 17 permits disclosure of professional secrecy upon written request of investigative, prosecutorial and judicial authorities, without an express proportionality test, without distinguishing categories of material (administrative facts, professional conclusions, clinical records, raw test data, third-party information) and without a procedure for contesting overbroad requests. Third, the law is silent on the governance of professional records – minimum content, retention, secure storage, access, transfer, destruction, data breaches – and on third-party commissioning, the everyday situation of schools, employers, courts and military bodies in which the person receiving the service is not the person paying for it. The Italian Code, by comparison, articulates minimum-necessary disclosure, document protection and a general five-year minimum retention for professional records. Recommendation R13 sets out the corresponding national standards.

4. The mental health needs of the nation

4.1. The measured crisis among university students

Recent (2024–2025) pilot multi-screening studies conducted at major Uzbek universities, including Tashkent State Pedagogical University, a partner of EduCATIA, reveal alarming statistics (Akharov & Khan, 2024; 2025): (a) a significant portion of students demonstrates high levels of anxiety, signs of emotional burnout and chronic stress; (b) 21.8% of students are at increased risk for suicidal behaviours; (c) 15.1% potentially require psychological support, with 1.3% reporting monthly self-harm; and (d) 3.6% of surveyed students have attempted suicide. A further 2024 study confirms that Uzbek students report high levels of perceived stress, with average scores above previously established norms for European students (Akharov & Khan, 2024). Despite this documented crisis, the 2025 report concludes that institutions in Uzbekistan lack organised counselling programmes, leaving students without essential psychological assistance, and identifies a significant lack of mental health support and academic advising.

The problem is officially acknowledged: the Ministry of Higher Education, Science and Innovation held a national seminar for HEI psychologists in late 2023 dedicated to the problems and solutions of the field, indicating system-wide awareness of the challenge. However, a systematic approach to psychological counselling programmes is lacking in Uzbek universities, as are strategies to monitor the impact of psychological support, and systematic training for psychologists tailored to the needs of higher education students is insufficient. Section 4.4 presents an Italian service model in which precisely these three elements – a structured counselling programme, an impact-monitoring architecture and a tailored professional format – have been operating and evaluated continuously for a decade.

4.2. The service gap: 222 higher education institutions

A systematic assessment conducted by the Uzbek partner HEIs across the entire set of 222 Uzbek higher education institutions found that 213 of them (95.9%) do not offer any psychological support service identifiable through their institutional websites. Only nine psychological units exist nationally, offering highly heterogeneous services mainly limited to individual support, and only rarely including workshops or proactive actions against the stigma associated with mental health conditions. With specific reference to the capacity to identify mental health vulnerabilities, only 2 of the 222 HEIs adopt psychodiagnostic services. In other words, the crucial mental health needs of the student population are currently determined only through national statistics: individual students have no services through which to understand their own vulnerabilities, and Uzbek HEIs offer no pathway from self-identification of need to psychological support. Universities located in remote territories additionally lack access to adequately qualified and certified professionals, and the absence of digital tools for psychological support further limits students' access to mental health services.

4.3. The Italian parallel: need, accessibility and the "psicologo di base"

The Italian experience shows that even in a mature professional system, need systematically outstrips accessibility, and that policy innovation follows measured demand. After COVID-19, demand for psychological support in Italy grew to the point of forcing structural responses: the State introduced a national voucher for psychotherapy (the so-called "bonus psicologo", Decree-Law 228/2021, Article 1-quater), whose applications exceeded available funds by an order of magnitude in every cycle – a direct measure of unmet need; several regions legislated the figure of the "psicologo di base" (primary-care psychologist), starting with Regione Campania (Regional Law 35/2020), to embed psychological assistance in primary care; and the Ministry of Education and the National Council of the Order of Psychologists (CNOP) signed a protocol (2020) to bring psychological support into schools during the pandemic, through micro-projects that markedly increased the permeability of the psychologist into the school system. The relevance for Uzbekistan is twofold: (i) demand for psychological assistance, once services become visible and destigmatised, reveals itself to be far larger than anticipated – Uzbekistan should plan capacity accordingly; (ii) the policy instruments that worked in Italy (primary-care embedding, school protocols, subsidised access) presuppose a sufficient supply of well-trained psychologists, which returns the problem to the degree and to its modernisation.

4.4. A validated model: the "WhatsApp e oltre" school listening service (Università Cattolica – ASAG)

The most directly transferable Italian experience for the purposes of this report is the project "WhatsApp e oltre: in ascolto della gener@zione digit@le, dalla multimedialità alla relazionalità (emotiva)", run since the 2014/2015 school year and renewed every year since – to the current 2024/2025 edition – by the Università Cattolica del Sacro Cuore through its Alta Scuola di Psicologia "Agostino Gemelli" (ASAG), together with ATS Milano Città Metropolitana and ASST Fatebenefratelli Sacco, and continuing a school-based prevention programme initiated in Milan in 1998 (Cavaliere, Gozzoli, Marranca, Pirovano & Tamanza, 2024). Its value for Uzbekistan is that it demonstrates, with a decade of continuity and published evaluation, that a psychological listening service embedded in educational institutions can be simultaneously a preventive intervention, a knowledge-production instrument and an object of impact evaluation – the three "souls" the authors attribute to the project, and precisely the three functions the Uzbek higher education system currently lacks.

The service model

- Low-threshold access. Students aged 14 to 21 access the listening desk freely, by appointment and free of charge, within their own school. The authors characterise the space explicitly as a low-threshold access point with a strong preventive value.
- Bounded intervention. Each pathway is capped at a maximum of four sessions. The intervention is expressly distinguished from a therapeutic relationship: it does not pursue treatment objectives.
- Explicit, teachable objectives. To give a name to anxiety, confusion and disorientation; to recognise the critical knots experienced as insurmountable obstacles; to help identify, alongside the constraints, the objective and subjective resources available; to attenuate prejudice towards psychological distress and to facilitate knowledge of and

access to the services existing in the territory; and to raise the threshold of attention to signs of distress.

- Structured professional infrastructure. Psychologists are selected by a joint Scientific-Technical Committee of the three partner institutions and have four weekly hours per desk, covering not only the consultations but their integration with school services, liaison with territorial and counselling services, and the re-elaboration of clinical and scientific material. Periodic small-group supervision on complex cases is a recognised component.
- Systematic documentation. The clinical record was purposely redesigned to include a process section enabling the psychologist to evaluate the outcome: number of sessions, degree of attainment of the objectives, referral and its acceptance, drop-out and its causes.
- The school as an actor, not a container. The psychologist works in close synergy with the institution, which is described as an active agent of prevention and wellbeing promotion rather than a mere host of the service, and the service extends to teachers and parents.

The evidence

Over the four school years 2020/21–2023/24 the service involved 2,503 adolescents across 191 desks, for a total of 10,050 student consultations, together with 929 consultations with teachers and 453 with parents – an average of roughly 30 schools, 48 desks and 859 students per year, with an average pathway of four sessions. Demand from adults grew markedly over the period (+42% for teacher consultations and +83.5% for parent consultations in the final year), indicating that a visible psychological presence progressively activates the whole educational community. Access was predominantly spontaneous, and the user profile shows a clear prevalence of female students (72.8% on average).

The evaluation of outcomes is itself the most instructive feature. Interventions failing to reach the intended objectives remained within a physiological range (10.2%–14.3%), objectives were fully attained in between roughly 30% and 50% of pathways – in 2022/23, 47.9% of pathways fully attained their objectives against 35.6% attaining them partially – and the pathway reached a physiological conclusion in 51.6%–64.7% of cases, with referral to another territorial service in 12.2%–19.9% and drop-out in 9.5%–20.4%. The authors read these figures, given the intrinsic limits of a four-session format and the developmental characteristics of the users, as a good result, and note that more than half of the pathways closing as planned indicates that the operational format is adequate to the needs it addresses. Where outcomes were less satisfactory, the causes were attributed mainly to weak motivation, personal resistance or excessively induced access, while difficulties in the psychologist–adolescent relationship (10.7%) and errors in defining the objective (14.3%) played a more limited role.

Why this model matters for Uzbekistan

Four features make this experience an appropriate reference for the psychological units to be established in the Uzbek partner HEIs. First, the low-threshold, capped, explicitly non-therapeutic format is realistic in a system where the profession has only just been established and where the supply of qualified psychologists is limited – it delivers early identification, de-stigmatisation and referral rather than attempting treatment at scale. Second, it makes referral an intended outcome rather than a failure: between one in eight and one in five pathways ends in a referral to a territorial service, which presupposes and builds a network that Uzbekistan will need to construct in parallel. Third, the built-in evaluation architecture – a clinical record designed from the outset to produce outcome data – is exactly the "strategy to monitor the impact of psychological support" that Section 4.1 identifies as missing in Uzbek HEIs, and it supplies the evidence base for the policy reform proposals of Section 8. Fourth, the service functions as a privileged observatory on the population it serves, generating the epidemiological knowledge that, in Uzbekistan, currently exists only as one-shot national statistics with no route from national data to individual support. The model is described here for secondary education; its transposition to the tertiary level – where Uzbek students present the vulnerabilities documented in Section 4.1 and where Article 10 of Law ZRU-989 does not yet reach – is the natural adaptation proposed in Recommendations R5 and R9.

4.5. The policy convergence: mental health reform and digitalisation

The Government of Uzbekistan has initiated sweeping, top-down reforms along two parallel tracks. On the mental health track, Law ZRU-989 (2024) professionalises psychological services and mandates psychological support in educational institutions; it is supported by the Presidential Decree on public mental health (June 2023) and Law ZRU-690 on mental health services (2021), which aim to integrate mental health into primary care and to increase the number of qualified specialists. On the digital track, the Digital Uzbekistan 2030 Strategy and the Concept for the Development of the Higher Education System until 2030 prioritise the integration of digital technologies, e-learning platforms and modern methods into education, and have already produced the widespread adoption of learning management systems across HEIs, a process accelerated by the COVID-19 pandemic; the Strategy for the Development of Artificial Intelligence Technologies until 2030 (Presidential Resolution PP-358, 14 October 2024) extends this track to AI. A significant gap persists between the two tracks: while HEIs rapidly digitalise academic delivery, student support services have not kept pace; and while the law mandates psychological support in educational institutions, the on-the-ground infrastructure remains underdeveloped. The modernisation of the psychology degree sits exactly at the intersection of the two tracks, and is aligned with the Erasmus+ CBHE regional priority for Central Asia ("Digital transformation") and with the EU Global Gateway cooperation priorities for Uzbekistan, which include digitalisation (EEAS, 2024), as well as with the EU policy framework set by the Communication "A comprehensive approach to mental health" (COM(2023) 298). Sections 4.6 and 4.7 develop this alignment in two directions: the permeability of the principles of the EU mental health framework into the Uzbek reform, and the anchoring of the strategy in the EU's financing architecture – the Global Gateway strategy and the country programming of the Multiannual Financial Framework 2021–2027.

4.6. The permeability of the principles of the EU mental health framework

The Communication "A comprehensive approach to mental health" (COM(2023) 298) is formally addressed to the EU institutions and Member States, but it is constructed to travel. Its three guiding principles – (i) access to adequate and effective prevention, (ii) access to high-quality and affordable mental healthcare and treatment, and (iii) the ability to reintegrate society after recovery – are formulated as universal design criteria for mental health systems rather than as EU-internal regulatory obligations. The Communication itself makes their external permeability explicit: its chapter on fostering mental health globally states that the EU intends to lead by example, to mainstream mental health in measures to strengthen health systems at regional, national and global level, and to make mental health and psychosocial support (MHPSS) an integral part of the strengthening of national health systems in partner countries. This external dimension is carried by two instruments that both apply to Uzbekistan's cooperation with the EU: the EU Global Health Strategy (COM(2022) 675), whose priorities include public health security together with mental health and psychosocial support, and the Youth Action Plan in EU external action 2022–2027 (JOIN(2022) 53), which places mental and physical well-being at the core of its "empower" pillar. The principles of COM(2023) 298 are therefore not merely a useful analogy for Uzbekistan: they are the declared standard that EU external cooperation applies when it supports partner-country health and education systems.

The permeability is also structural. The first operating principle of the Communication – mental health across all policies – holds that obstacles to good mental health cannot be overcome within the health system alone, and that education, employment, digital and social policies must carry the mental health objective jointly. This is precisely the configuration of the Uzbek reform described in Section 4.5: a mental health track (Law ZRU-690, the 2023 Presidential Decree, Law ZRU-989) and a digital-education track (Digital Uzbekistan 2030, the Higher Education Concept 2030, Resolution PP-358) that currently run in parallel and must converge. The modernised psychology degree is the natural point of convergence, and the three principles map onto the Uzbek framework – and onto the recommendations of Section 8 – with unusual precision.

Prevention. The Communication identifies schools and other educational settings as key places for promotion, prevention and early intervention, and makes adequately trained staff the condition for their effectiveness; its flagship initiatives concentrate on depression and suicide prevention and on child and youth mental health. In Uzbekistan, Article 10 of Law ZRU-989 already mandates psychological services in pre-school, secondary and professional education, and the measured situation of the student population – 21.8% of surveyed students at increased suicidal risk (Section 4.1) – places the country squarely within the priority the Communication assigns to young people. What the Uzbek framework lacks is not the mandate but the trained preventive workforce and the extension of the mandate to higher education (R9); the degree, modernised along R1–R5, is the instrument that supplies both.

Access to care. The Communication explicitly instructs that the use of digital tools – telemedicine and advice hotlines – should be explored for people requiring better information and care, including in rural areas, and dedicates a flagship initiative to more and better trained professionals, including a cross-border exchange programme. Transposed to Uzbekistan, this is the argument of Sections 4.2 and 5.2: with 222 higher education institutions and services in only a handful of them, and with a 3.6-fold regional income differential, digitally delivered psychological support is the only realistic route to territorially equitable access in the medium term, and the training of professionals – initial (the degree) and continuous (R7) – is the binding constraint. The EU's own policy therefore validates, at the level of principle, the digital orientation of the modernisation.

Reintegration. The third principle – reintegration into society after recovery, coupled with the Communication's chapter on breaking through stigma – addresses the dimension of the Uzbek framework that is least developed: Law ZRU-989 regulates the provision of assistance but is largely silent on stigma, social inclusion and return to study or work. A profession trained in deontology (R4), embedded in educational institutions (R5, R9) and equipped to run structured awareness programmes at scale through digital platforms (Section 5.2) is the operational form that this principle takes in the Uzbek context. The permeability of the three principles is thus complete: each finds an existing legal anchor in the Uzbek reform, a measured need in the national data, and a corresponding recommendation in Section 8.

4.7. Anchoring the strategy in Global Gateway and the Multiannual Financial Framework: the MIP 2021–2027 for Uzbekistan

The alignment described above is not only one of principle; it is also one of financing architecture. COM(2023) 298 states that the Commission is mobilising all relevant financial instruments of the EU budget under the 2021–2027 Multiannual Financial Framework (MFF) to address mental health challenges, identifying EUR 1.23 billion of EU support. For a non-EU partner country, the MFF reaches the national level through the external action instrument NDICI–Global Europe, whose country-level programming for Uzbekistan is set out in the Multi-annual Indicative Programme (MIP) 2021–2027 (C(2021) 9137). The Global Gateway strategy (JOIN(2021) 30) is the investment framework through which this programming is increasingly delivered, and its cooperation priorities agreed with Uzbekistan explicitly include digitalisation (EEAS, 2024). A note on terminology for the authors: the instrument sometimes referred to in project drafts as the "Multiannual Financial Framework in Uzbekistan" is, correctly, the country MIP 2021–2027, i.e. the programming document that translates the EU's MFF-funded external instrument into priorities for Uzbekistan; the MFF itself is the EU's overall seven-year budget.

The MIP offers three concrete anchor points for the degree modernisation strategy. First, its Priority Area 2, "Inclusive, digital and green growth", contains a dedicated specific objective on skills development for decent jobs and digital literacy, and commits the EU to supporting partnerships with European higher education institutions to increase digital access and literacy under the "Digital Uzbekistan 2030" reform, with the digital skills of women and youth in rural areas expressly prioritised in order to diminish the digital and educational divide between rural and urban populations. This is, almost verbatim, the equity argument of Section 5.2: a digitally competent, predominantly female psychological profession delivering services across regional divides. Second, the MIP mainstreams gender equality, youth, digitalisation and support to vulnerable groups as cross-cutting priorities across all its priority areas, so that a modernisation of the psychology degree oriented to digital competences and to the staffing of student services scores simultaneously on several axes of the EU's intervention framework. Third, the MIP's cooperation facility explicitly serves to promote Uzbekistan's participation in EU programmes, naming Erasmus+ and Horizon Europe, and to foster a dedicated education-focused dialogue with the Government and stronger linkages with the Erasmus+ scheme; EduCATIA, as an Erasmus+ Capacity Building in Higher Education action, sits exactly in this window and can legitimately present itself as an implementing vehicle of the MIP's education and digitalisation commitments.

For Global Gateway, the connection runs through the human development and digital pillars of the strategy: Global Gateway finances not only hard infrastructure but the skills, standards and regulatory convergence that make infrastructure usable, and the EU–Uzbekistan cooperation priorities agreed in the Sub-committee for Development Cooperation (EEAS, 2024) place digitalisation among them. A modernised psychology degree that trains professionals to deliver services through digital infrastructure, under European deontological and data-protection standards (Sections 3 and 6), is a textbook soft-infrastructure complement to that agenda. Framing the modernisation in these terms – the principles of COM(2023) 298 as the policy standard, Global Gateway as the investment framework, and the MIP 2021–2027 as the programming instrument – gives the recommendations of Section 8 a documented pathway to EU financing and political support, including in the perspective of the Enhanced Partnership and Cooperation Agreement and of the GSP+ monitoring dialogue, both of which the MIP identifies as drivers of the EU–Uzbekistan relationship.

5. The digital revolution in psychology

5.1. From exception to mainstream

Until recently, digital delivery was often not considered a real option for psychological practice in Italy: technology-mediated assistance was viewed with caution by parts of the profession, and the professional debate on its legitimacy, efficacy and deontological boundaries remained open [ref. Spisni – TO COMPLETE]. Three forces changed this position. First, the COVID-19 pandemic forced the transition: social distancing made technology-mediated assistance the only available channel, compelling practitioners, regulators and clients to adopt it at scale, and the professional bodies to regulate rather than resist it. Second, the evidence matured: several meta-analyses show no significant differences in outcomes between online and face-to-face psychological support for a wide range of conditions, with comparable efficacy and, in substance, absence of additional risks when standards are respected. Third, the market organised itself: digital platforms for psychological support became mainstream, with widely used Italian models such as UnoBravo, Serenis and Sygmund; the leading Italian provider, UnoBravo, employs around 7,000 psychologists and serves over 300,000 patients. The professional debate has not disappeared – questions of therapeutic alliance at a distance, emergency management and platform labour conditions remain legitimately discussed within the profession – but the centre of gravity has moved from whether to how.

5.2. Why digitalisation is an opportunity: the evidence

Published Social Impact reporting of the Italian digital providers, together with sector statistics, documents seven properties of digitalised psychological support of direct relevance for Uzbekistan:

- Equivalent outcomes. There are no significant differences in outcomes between online and face-to-face psychological support, as shown by several meta-analyses.

- Accessibility. Digital delivery removes geographical barriers, reaching users in territories without qualified professionals – the exact condition of remote Uzbek regions (Section 4.2).
- Measurability. Client satisfaction and outcomes can be anonymised and updated in real time, continuously enriching databases for impact measurement – a property that also enables the evidence-based policy making that the Uzbek reform requires. The anonymised-data clause of Article 17 of Law ZRU-989 explicitly permits such use for quality improvement and training.
- Privacy and confidentiality. Properly designed digital applications can ensure the privacy and confidentiality of participants, in line with Article 17 of Law ZRU-989.
- Awareness at scale. Digital platforms allow structured sensitisation and awareness programmes on mental health, the missing proactive component of the few existing Uzbek units (Section 4.2).
- Environmental sustainability. Digitalised services minimise environmental impact through remote work and reduced travel, digitalised documentation, and low-emission server infrastructure.
- Social and territorial equity. The 2024 UnoBravo Social Impact Report shows that digital psychological support improved the social and economic equity of psychologists in Italy. The Italian National Social Security Entity for Psychologists (ENPAP, 2024) identified a strong regional pay gap – an average annual income of €13,339 in Campania against €26,077 in Lombardy, a difference of up to 48.8% – whereas psychologists working through digital services earn comparable incomes across regions (€26,695 on average in the UnoBravo report). The same mechanism addresses gender inequity: at national level male psychologists earn on average 20% more than female psychologists (ENPAP, 2024), whereas digital platforms show substantially equal incomes (€27,679 for female and €25,711 for male psychologists in the UnoBravo 2024 report).

The equity argument transfers directly to Uzbekistan. Regional GDP per capita differs markedly among regions: Tashkent City reports 91,376,600 UZS per year (€6,494) against 25,452,400 UZS (€1,809) in the Khorezm region – a 3.6-fold difference (Statistics Agency under the President of the Republic of Uzbekistan, 2025). Gender inequality is also pronounced: female employment stands at 39.4% against 72.3% for men (World Bank Gender Data Portal, 2024), and UNECE (2024) identifies a gender pay gap of 36%. Digital psychology, by applying unified methodologies and socially equitable pricing, promotes territorial and gender equity in both access to services and professional income – in line with EU values of equality. Since psychology in Uzbekistan, as in Italy, is a profession with strong female participation, the modernisation of the degree towards digital competences is also, concretely, a gender-equality measure.

5.3. The school transformation

COVID-19 also forced greater permeability of the psychologist in the school environment. In Italy, the protocol between the Ministry of Education and the CNOP (2020) and the associated micro-projects funded during the pandemic period placed psychologists in schools at scale for the first time, normalising the presence of psychological support in educational settings. Uzbekistan is legislatively ahead on this specific point: Article 10 of Law ZRU-989 already mandates psychological services in pre-school, general secondary, secondary specialised and professional educational organisations. What is missing is (i) the extension to higher education and (ii) the trained workforce to staff these services – both of which depend on the degree. The "WhatsApp e oltre" experience (Section 4.4) shows what a mature version of the Article 10 model looks like in practice: a stable, evaluated, low-threshold service networked with territorial health services and with the school itself as an active partner. The Italian experience of the "psicologo di base" further shows the direction of travel: psychological assistance embedded in ordinary public services, staffed by professionals trained to standardised competence profiles.

6. Artificial intelligence in psychology and in psychology education

6.1. The EU AI Act: lawful and unlawful uses of AI in psychology

Regulation (EU) 2024/1689 (the AI Act) is the world's first comprehensive horizontal regulation of artificial intelligence and constitutes the natural reference framework for the modernisation of a psychology degree, because several of its provisions target precisely the psychological domain:

- Prohibited practices (Article 5). The AI Act prohibits, among others: AI systems deploying subliminal or purposefully manipulative techniques that materially distort behaviour causing significant harm; systems exploiting vulnerabilities due to age, disability or social and economic situation; and – of direct psychological relevance – AI systems that infer emotions of natural persons in the workplace and in education institutions, except for medical or safety reasons (Article 5(1)(f)). Emotion-recognition systems outside these contexts, and any use within them not covered by the medical/safety exception, are unlawful in the EU.
- High-risk systems (Article 6 and Annex III). AI systems used in education and vocational training (determining access, evaluating learning outcomes, monitoring prohibited behaviour during tests), in employment (recruitment, evaluation), and in essential services including healthcare triage, are classified as high risk, with obligations of risk management, data governance, transparency, human oversight, accuracy and robustness.
- Transparency (Article 50). Persons interacting with an AI system such as a chatbot must be informed that they are interacting with a machine – a rule of evident importance for mental-health chatbots and digital psychological interventions.

Read together, these provisions draw a usable map of lawful and unlawful AI uses in psychology: AI as a support tool for the professional (documentation, literature analysis, data processing, psychometric scoring under human oversight) is lawful and encouraged; AI as an autonomous evaluator of persons in education and work contexts is high-risk and strictly conditioned; AI as an emotion-inference engine in schools and workplaces is prohibited; AI presenting itself as a therapeutic interlocutor without transparency is unlawful. Uzbekistan currently has no equivalent legislation: the Strategy for the Development of Artificial Intelligence Technologies until 2030 (PP-358, 14 October 2024) is a development strategy – setting targets such as $1.5 billion of AI-based services, ten AI laboratories and a top-50 position in the Government AI Readiness Index, and including the formation of a regulatory framework among its priority tasks – but it does not yet regulate AI uses, and Law ZRU-989 regulates methodologies of psychological assistance (Article 7) without addressing AI specifically. The Ministry of Health standards under Article 7, and the codes of ethics under Article 12, are the natural vehicles through which AI-Act-inspired rules (prohibition of manipulative and emotion-inference systems in sensitive contexts, transparency of chatbots, human oversight of assessment) can enter the Uzbek psychological profession. The degree should train the professionals who will write and apply them.

6.2. The EU Guidelines on the ethical use of AI and data in teaching and learning

For the educational use of AI, the reference instrument is the European Commission's Guidelines on the ethical use of artificial intelligence and data in teaching and learning for educators, revised edition (manuscript completed November 2025; Publications Office of the European Union, 2026), which supersede the first 2022 edition and were produced through the Working Group on Ethical Use of AI and Data in Education convened by the European Digital Education Hub. The guidelines are non-binding and are addressed primarily to teachers and school leaders in primary and secondary education; they explicitly state, however, that policymakers and providers of continuing professional development can draw on the full document to inform strategic planning and professional learning design – which is precisely the use made of them here. They are organised in three parts: core principles and legal context (AI Act, GDPR and the underpinning ethical considerations); guiding questions and scenarios; and background resources.

Three elements of the revised edition are directly transferable to the modernisation of the Uzbek psychology degree.

First, the five ethical considerations that underpin the ethical use of AI and data in teaching, learning and assessment, informed by the Ethics Guidelines for Trustworthy AI: human dignity (privacy, autonomy and agency, and the recognition of each individual's intrinsic value rather than treating people as data objects); fairness (equity, inclusion, non-discrimination); trust and trustworthiness (explicitly including the vulnerability of learners, power dynamics and critical thinking); academic integrity (honest use, proper attribution, and assessment design that remains valid in the era of generative AI); and justified choice (transparency, explainability and participatory decision-making). The vulnerability and power-dynamics dimension of trustworthiness maps almost exactly onto the professional ethics of psychology, where the asymmetry between practitioner and client is the founding reason for the deontological framework.

Second, the eight dimensions of guiding questions, each articulated on two levels – for the teacher and for the institution: human agency and oversight; transparency and explainability; diversity and inclusion; fairness and non-discrimination; societal and environmental wellbeing; privacy and data governance; technical robustness and safety; and accountability. The guidelines specify that a negative answer to a guiding question does not block the use of a tool but signals that further action is needed, such as seeking clarification from providers or putting additional safeguards in place. This two-level, question-based architecture is the single most reusable feature of the document for Uzbekistan: it can be transposed, with the adaptations set out below, into the institutional protocol of the HEI psychological units and into the assessment tasks of the proposed AI module.

Guiding-question dimension	**Question in the EU guidelines (illustrative)**	**Transposition to psychology training and psychological units**
Human agency and oversight	Can I detect if the AI has made a mistake or an inappropriate suggestion? Who is responsible for reviewing and validating AI outputs?	Who validates an AI-supported screening result before it reaches the student? No automated output may reach a client without a named professional having reviewed it (cf. Arts. 14 and 16, ZRU-989)
Transparency and explainability	Has the provider supplied clear documentation on how the tool works, including its decision logic?	Documented decision logic is a precondition for any digital screening instrument adopted by a psychological unit; students must be informed of the role of AI in any assessment
Diversity and inclusion	Are different languages, cultural contexts, genders and abilities adequately represented? Is there an option for low-bandwidth or offline access?	Uzbek/Russian language coverage and low-bandwidth access are decisive for the remote regions identified in Section 4.2; instruments validated on other populations require local validation
Fairness and non-discrimination	Has the tool been tested for bias across different learner groups before adoption?	Bias testing of any automated mental-health screening across gender, region, language and socio-economic groups before deployment
Societal and environmental wellbeing	Have I noticed whether AI use affects students' motivation or mood (e.g. anxiety, disinterest, dependence)? What boundaries maintain meaningful human interaction?	The dependence and human-interaction question is the core clinical issue of digital psychological support: boundaries between AI-supported orientation and human professional contact must be explicit
Privacy and data governance	Do I avoid inputting sensitive or personally identifiable information into AI tools? Is learner data stored securely and	Directly enforceable through Art. 17 of ZRU-989: psychological data are professional secret equated to medical confidentiality; general-

	used solely for its intended purpose?	purpose AI tools must never receive client material
Technical robustness and safety	Has the institution established a formal procedure for reporting unsafe outputs, and a response plan including student safeguarding?	Crisis-escalation and safeguarding protocol for any digital or AI-supported psychological service – the single non-negotiable safety requirement of a pilot
Accountability	Does the institution have a clear division of responsibilities and a process for complaints and redress?	Named clinical responsibility within the psychological unit; complaint route consistent with the disciplinary powers of the public associations of psychologists (Art. 12, ZRU-989)

Third, the institutional planning sequence recommended by the guidelines: review current AI tools and data use; establish AI and data policies and procedures (including data-protection and fundamental-rights impact assessments, procurement of trustworthy and human-centric tools, verification that input data are appropriate to the intended purpose, mechanisms for meaningful human oversight, monitoring with corrective measures, and staff training); pilot the tool with a defined cohort against explicit evaluation criteria; maintain a documented relationship with the provider, including a service-level agreement; monitor operation and re-evaluate risk on an ongoing basis; communicate with learners and families, encouraging acknowledgement of AI use particularly in assessment; and sustain professional learning for responsible AI integration. This sequence is a ready-made governance template for the psychological units to be established in the partner universities.

The guidelines also connect ethical use to competence frameworks: DigComp 3.0 (2025), which systematically integrates AI competence into the European Digital Competence Framework; DigCompEdu, which describes the competences educators need and the organisational capacity institutions require; the SELFIE for Teachers self-reflection tool; and the AI Literacy (AILit) Framework, a joint European Commission–OECD initiative whose review draft (May 2025) sets out 22 competences across four domains – engaging with AI, creating with AI, managing AI and designing AI – and is to be finalised in 2026. Together with the AI Act's own definition of AI literacy (Article 3(56)) and the Article 4 obligation on providers and deployers to ensure a sufficient level of AI literacy among staff, these frameworks supply the competence scaffolding for the module and the train-the-trainer pathway proposed in Section 8.

Comparison with the Uzbek framework: Resolution PP-358 read against the EU guidelines

The relevant Uzbek instrument is Presidential Resolution PP-358 of 14 October 2024, approving the Strategy for the Development of Artificial Intelligence Technologies until 2030, together with its Action Plan and appendices (this analysis is based on the official Russian text and the unofficial English translation). The two instruments are different in kind before they are different in content. The EU guidelines are non-binding pedagogical guidance addressed to teachers and institutions, resting on binding law (the AI Act and the GDPR) and operating through guiding questions that place the ethical judgement in the hands of the educator. PP-358 is a binding presidential resolution approving a national development strategy whose logic is industrial: its target indicators are USD 1.5 billion of AI-based software products and services, a top-50 position in the Government AI Readiness Index, ten research laboratories with high-performance computing, and a 10% share of AI-based services on the unified public services portal. In PP-358, ethics appears not as content but as a scheduled task: the resolution mandates the future development of ethical requirements rather than articulating them.

That scheduling is nonetheless precise, and it matters for EduCATIA. Among the Strategy's priority objectives, the first – developing the legal framework – includes "establishing security and ethical requirements for artificial intelligence technologies", implemented through the measure "developing ethical guidelines for artificial intelligence technologies". The Action Plan then operationalises this in Task 2 ("Formulating ethical rules and principles for the development and application of artificial intelligence technologies", Ministry of Digital Technologies with the relevant ministries): analysis of international experience – explicitly including the prioritisation of the protection of human interests and rights, and ethical guidelines regulating the principles of application – by October 2025; drafting of a regulatory-legal document by December 2025; submission to the Cabinet of Ministers by January 2026. Task 3 follows the same sequence for a regulatory-legal document on the security of personal data in the development and use of AI, "based on advanced international practices", due to the Cabinet of Ministers by December 2025. Uzbekistan has therefore chosen the mirror-image architecture of the EU: a single, economy-wide, binding ethics regulation drafted centrally, rather than sector-specific professional guidance resting on horizontal law; and nothing in the pipeline is education-specific. Note for the authors: the Action Plan deadlines have now passed – the adoption status of the Task 2 and Task 3 regulatory documents should be verified with the Uzbek partners; if the drafting process is still open, it constitutes a direct window of opportunity, since PP-358 itself mandates the analysis of international experience of exactly the kind the EU guidelines codify.

The education provisions of PP-358 sharpen the comparison. In its sectoral chapter on education, culture and tourism, the Strategy lists as deployment targets: monitoring students' attendance and ensuring their safety through biometric identification technologies in educational institutions; identifying gaps in learning across subjects and grades and analysing students' intellectual and physical development; automating the assessment of knowledge and analysing educational outcomes; expanding opportunities to learn programming and AI; and game-based programmes for children. Read through the EU lens, these targets fall into sharply different categories. Automated assessment of knowledge and the evaluation of learning outcomes belong to the education use cases the AI Act classifies as high-risk – permitted, but only with human oversight, transparency and documented accountability, precisely the matters interrogated by the guidelines' guiding questions. Biometric attendance monitoring engages the guidelines' privacy and data-governance dimension and the GDPR proportionality test – European data protection authorities have repeatedly found facial-recognition attendance systems in schools disproportionate to their purpose – and any drift of such systems towards inferring the emotional state of students would cross the prohibition of Article 5(1)(f) of the AI Act, which, as noted above, applies to education and training institutions at all levels regardless of the students' age or mode of learning. The programming, AI-education and game-based measures, by contrast, are fully convergent with the EU's AI-literacy agenda. PP-358 lists all of these deployments without accompanying safeguard language: the governance layer is deferred entirely to the Task 2 ethics document, which is not education-specific. The narrow role-play exception of the AI Act remains of direct interest for psychology teaching: emotion-recognition systems used for learning purposes in role-play, for example in training future practitioners, are permitted only if the results cannot impact the evaluation or certification of the person being trained – a precise rule for the counselling-simulation exercises that a modernised curriculum would naturally use.

On data governance, the divergence is structural. PP-358 constructs a centralised "Big Data" database: ministries and agencies must transfer the datasets listed in Appendix 3 – including education data – to the Ministry of Digital Technologies "in compliance with the legal requirements on personal data (including anonymization of data where applicable)", for use in projects and scientific-practical research. The guidelines' logic runs in the opposite direction: purpose limitation, data minimisation, learner data stored securely and used solely for its intended purpose, and the instruction never to input sensitive or personally identifiable information into AI tools. For the psychological units proposed in this report, the operational consequence is categorical: psychological data are professional secret under Article 17 of Law ZRU-989, equated to medical confidentiality, and must therefore remain outside any general data-pooling pipeline; only genuinely anonymised, aggregated indicators – of the kind Article 17 itself permits for quality improvement and training (Section 5.2) – may ever feed institutional or national datasets.

Finally, on AI literacy, PP-358 invests heavily in the specialist pipeline – AI courses in 15 HEIs since 2021/2022 under Resolution PQ-4996, 572 students admitted to dedicated AI programmes in 12 HEIs from 2023/2024, university laboratories for robotics, IoT and AI, free online courses with foreign professors, and the strengthening of mathematics and programming – and, more generically, in the digital skills of the population and the upskilling of "teachers and professors". What it does not contain is any analogue of DigCompEdu, DigComp 3.0 or the AILit Framework: a competence framework describing what a non-specialist educator – or a psychologist – must know in order to use AI responsibly. In AILit terms, PP-358 covers "creating with AI" comprehensively and leaves "engaging with AI" and "managing AI" unaddressed. That absence is exactly the space in which Recommendations R1 (the AI-in-psychology module) and R6 (the digital train-the-trainer programme) operate, and the teacher-upskilling commitment of PP-358 gives them a national policy anchor. The synoptic comparison is as follows:

Dimension	EU Guidelines on the ethical use of AI and data (2026, rev. ed.)	Uzbekistan – Resolution PP-358 (14 October 2024)
Legal nature	Non-binding guidance for educators and institutions, resting on binding horizontal law (AI Act, GDPR)	Binding presidential resolution approving a development strategy; ethical requirements delegated to a future economy-wide regulatory document (Action Plan Task 2, due to

		the Cabinet of Ministers by January 2026)
Addressees	Teachers and school leaders primarily; policymakers and CPD providers secondarily	Ministries and agencies, coordinated by the Ministry of Digital Technologies; educators are not addressed as ethical decision-makers
Ethical principles	Five articulated considerations: human dignity, fairness, trust and trustworthiness, academic integrity, justified choice	"Protection of human interests and rights" named as a drafting criterion for future rules; principles not yet articulated
Education-specific rules	Eight guiding-question dimensions, each at teacher and institution level; scenarios and planning sequence	Education listed as an application sector (biometric attendance monitoring, learning-gap analytics, automated assessment, AI education, games for children) without accompanying safeguards
Risk logic	AI Act categories incorporated: prohibited practices (incl. emotion inference in education), high-risk education uses with human-oversight and transparency duties	No risk classification; deployment targets and indicators only
Data governance	Purpose limitation, data minimisation, secure storage, no sensitive data into AI tools, learner data used solely for intended purposes	Centralised "Big Data" pooling of ministerial datasets (incl. education) with anonymisation "where applicable"; dedicated personal-data security document scheduled (Task 3)
AI literacy	DigComp 3.0, DigCompEdu, AILit Framework, SELFIE for Teachers; Article 4 AI Act literacy obligation	Specialist pipeline (dedicated AI degrees, labs, foreign courses) and general digital skills; upskilling of teachers foreseen, but no educator competence framework
Institutional governance	Planning sequence for HEIs/schools: review, policies and impact assessments, pilot, provider SLA, monitoring, communication with learners	Programme-level governance (Coordination Commission, Center for the Development of AI and the Digital Economy, USD 50 million loan); no institutional AI-use protocol for HEIs

The comparison, in sum, is one of sequencing rather than of incompatibility. PP-358 mandates precisely the exercise – the study of international experience in the protection of human rights in AI and in ethical guidelines for its application – for which the EU guidelines are the most developed education-sector corpus available; and until the national ethics layer exists, the institutional protocol derived from the guidelines in this section, together with the module and train-the-trainer pathway of Recommendations R1 and R6, allows the partner universities to implement an EU-grade governance layer at institutional level without waiting for the national instrument. This is also the reading most favourable to the Uzbek authorities: the guidelines are offered not as an external benchmark against which PP-358 falls short, but as ready-made input into a drafting process that the resolution itself has already commissioned.

6.3. Risks of AI in the psychological domain

Three risk families must be explicitly addressed in the modernised curriculum, because they are already materialising:

- AI as a substitute for the psychologist in the eyes of the user. Students and young people increasingly turn to general-purpose conversational AI for emotional support. The risk is not hypothetical: documented litigation in the United States concerns minors and young users who discussed suicidal ideation with AI chatbots and subsequently died by suicide, with the systems failing to interrupt the interaction or effectively redirect the person to human help, and in the most serious allegations providing method-relevant information. Whatever the outcome of individual cases, they demonstrate the category of harm: persuasive, empathic-sounding systems, available continuously and without gatekeeping, can absorb the help-seeking of vulnerable users without any of the safeguards, competence or responsibility of the profession that Law ZRU-989 has just established. The EduCATIA needs analysis reaches the same conclusion from the pedagogical side: students must understand that persuasive or empathic language generated by a system does not demonstrate psychological understanding, clinical competence or therapeutic responsibility, and any pilot involving AI-supported psychological orientation must be limited to low-risk uses, with direct access to qualified professionals and explicit crisis-escalation procedures.
- AI for diagnosis and testing. Is AI-based assessment effective? Can it substitute psychometric testing? Is it deontologically admissible? The current evidence supports a precise answer: AI tools can assist assessment (scoring, pattern detection, report drafting) but automated interpretation has unresolved problems of validity, reliability and bias – particularly against cultural, linguistic and minority groups – and unsupervised AI diagnosis violates both the EU high-risk regime and the competence and responsibility principles of every deontological code, including Articles 14 and 16 of Law ZRU-989. The curriculum must teach the validity conditions of automated assessment, not merely its tools.
- AI as delegation of professional judgement. The subtlest risk is the psychologist who asks the AI instead of evaluating personally – decision delegation. Human oversight, in the AI Act sense, requires the professional to remain capable of overriding, contesting and explaining any AI-supported conclusion. This capability is trainable, and the degree is where it must be trained: through ethical case analysis, validation exercises on automated interpretations, identification of misleading psychological claims, and structured comparison between AI-supported and professionally supervised assessment.

6.4. What the EduCATIA needs analysis shows for psychology

The EduCATIA questionnaires (68 psychology students and 46 psychology teachers; exploratory sample) document, for the psychological sciences, the largest adoption–institutionalisation gap of the project: 82.6% of psychology teachers and 47.1% of psychology students use AI often or always, but only about a third of each group has received university training (32.6% of teachers; 33.8% of students), only 32.4% of students report field-specific AI teaching, and only 47.8% of teachers report transferring field-specific competence. Demand for structured learning is high in both groups (69.6% of teachers and 66.2% of students want further field-specific competence), and the use of AI for accessibility and support of students with fewer opportunities is comparatively low among psychology teachers (34.8%). The report concludes that practical adoption is progressing faster than structured professional integration – a particularly sensitive condition in a discipline dealing with highly personal data, assessment of mental states, predictions about vulnerable individuals and professional decisions with significant consequences – and recommends a dedicated pathway covering behavioural-data analysis, psychological and neuropsychological assessment, cognitive modelling, neuroimaging analysis, affective computing and emotion-recognition systems, mental-health chatbots and digital interventions, validity and reliability of automated assessment, bias, privacy and informed consent, limits of prediction, professional supervision, crisis escalation and referral, and the boundary between support and therapy.

6.5. What is taught in Italy, and the train-the-trainer gap in Uzbekistan

In Italy, AI-related content is entering psychology education along three channels: dedicated modules within LM-51 Master's programmes (new technologies for psychology, digital mental health, AI and behaviour, psychometrics with computational methods); post-graduate and continuing education courses on digital psychology and AI-assisted practice, increasingly offered by universities and recognised bodies; and the transversal integration of AI-literacy content prompted by the AI Act's entry into application, which requires professional users of AI systems to possess adequate AI literacy (Article 4). No equivalent channel currently exists in Uzbekistan for psychology: crucially, there is a substantial absence of train-the-trainer provision for professors of psychology – the professors who should teach AI-related competences have themselves had no structured opportunity to acquire them, as the EduCATIA data confirm (32.6% trained). The solution must be digital and replicable: a train-the-trainer programme delivered through a digital platform, producing reusable open educational resources, so that the capacity built in the partner universities propagates to the remaining Uzbek HEIs at marginal cost.

6.6. Psychologists in the universities themselves

Finally, the analysis must register a reflexive gap: the substantial absence of psychologists in university contexts. The participating Uzbek universities do not include psychological support units, reflecting the national situation (Section 4.2), and Law ZRU-989 does not extend its educational mandate (Article 10) to HEIs. Policies promoting the presence of the psychologist at the university level should be actively supported: they simultaneously address the measured student mental health crisis, create the internship placements that the modernised degree requires, and build the employment demand that justifies the degree's expansion into digital and AI-supported practice.

7. Consolidated gap analysis

The table below consolidates the analysis, mapping each requirement or need identified in the law and in the evidence base against the current provision of the degree.

Requirement / need (source)	**Law ZRU-989**	**Current degree 60310300**	**Gap**
ICT-mediated psychological assistance (Art. 6)	Explicitly permitted	No digital/tele-psychology content; one generic ICT course	No training for a legally permitted form of practice
Authorised methodologies and standards (Art. 7)	Ministry of Health standards; permitted methods only	No course on professional law, standards or deontology	Graduates unprepared for the regulatory regime governing them
Psychological services in educational organisations (Art. 10)	Mandatory in pre-tertiary education	Internships not anchored to service units; HEIs excluded from Art. 10	Workforce and placement gap; tertiary blind spot
Competence boundary and refusal duty (Arts. 14, 16)	Refusal required outside own competence	No specialisation profiles; no digital deontology	Competence self-assessment untrained
Confidentiality equated to medical secrecy (Art. 17)	Strict regime; anonymised use for training/quality	No data-protection or research-ethics module beyond Art. 11 basics	Privacy/data governance competence missing
Psychodiagnostics (retraining route omits it; only 2/222 HEIs offer it)	Examination is a defined type of assistance	10+6 credits – a strength, but analog-only	Digital and automated assessment validity not covered
Continuous professional development (absent from law)	Not regulated	Not addressed	No CPD system; obsolescence risk, esp. for retrained professionals
Student mental health crisis (Akharov & Khan 2024; 2025)	Not addressed for HEIs	No practicum in student services; no crisis/escalation training	Measured need unmet by both law and degree

AI adoption without governance (EduCATIA data; AI Act benchmark)	Not addressed	No AI content at all	Largest single modernisation gap
Train-the-trainer for psychology professors	Not addressed	Not addressed	Precondition of every other reform

Beyond the requirements mapped above, the compulsory catalogue also fails to expressly identify dedicated modules in psychopathology, psychobiology or behavioural neuroscience, neuropsychology, safeguarding and suicide-risk management, and evidence-based psychological intervention. These absences do not alter the gap matrix – they concern the scientific rather than the regulatory core – but they should inform the planning of the 40-credit elective block alongside the digital and deontological modules of R1–R4, and the safeguarding and suicide-risk content in particular should be treated as compulsory within any pathway leading to work in educational settings, given the prevalence data of Section 4.1.

8. Recommendations for the modernisation of the degree

The following recommendations are formulated for the partner universities and, where indicated, for the competent national authorities. They are designed to be implementable within the existing 240-credit architecture, primarily through the 40-credit elective block and the internship structure, without requiring the reopening of the compulsory core.

R1. Introduce a module on “Artificial Intelligence in Psychology”

A dedicated module – initially elective, with a roadmap towards mandatory status – delivered digitally so as to be replicable across all Uzbek HEIs, covering the pathway recommended by the EduCATIA needs analysis: behavioural-data analysis; AI-assisted psychological and neuropsychological assessment and its validity conditions; cognitive modelling; affective computing and the EU prohibition of emotion inference in education and work contexts; mental-health chatbots and digital interventions, with transparency and crisis-escalation requirements; bias, privacy and informed consent; limits of prediction; human oversight and the non-delegation of professional judgement. Igor Vitale International S.r.l. can contribute to the design and digital delivery of this module, building on its European project experience. Learning activities should privilege ethical case analysis and structured comparison between AI-supported and professionally supervised assessment, and should adopt as an assessed instrument the two-level guiding-question architecture of the revised EU guidelines (Section 6.2), transposed to psychological practice. Competence design should be aligned with the AILit domains (engaging, creating, managing and designing with AI) and with DigComp 3.0.

R2. Introduce a module on “Digital Psychology and Tele-psychological Assistance”

Training for the ICT-mediated forms of assistance that Article 6 of Law ZRU-989 already permits: setting and alliance in remote practice, identity verification, data security, remote emergency management, platform-based service models and their evidence base (efficacy equivalence, accessibility, measurability, equity), with the Italian digital providers as documented case studies.

R3. Strengthen and digitalise psychodiagnostics

Preserve the existing 16 credits of psychodiagnostics and data-processing as the degree's distinctive strength, and extend them with computerised and adaptive testing, digital test administration and scoring under human oversight, and the validity and bias problems of automated interpretation. This directly addresses the national psychodiagnostic capacity gap (2 of 222 HEIs) and sharpens the competence differential that justifies the valorisation of the degree over the retraining route.

R4. Introduce "Professional Law and Deontology of the Psychologist"

A module anchored to Law ZRU-989 (types of assistance, standards, contracts, confidentiality under Article 17, refusal duties, title protection), to the codes of ethics of the public associations of psychologists, and to the comparative European framework (Law 56/1989; the CDPI as current comparative reference text; EFPA Meta-Code; EuroPsy). The syllabus should follow the article-level map of Section 3.3: extension of all deontological duties to distance practice (CDPI Art. 1); competence limits and continuing education as a deontological duty (Art. 5); validity and reliability of data, instruments and interpretations, including AI-assisted ones (Arts. 7 and 25); professional secrecy, derogations for grave danger to life, document protection and retention (Arts. 11–17); documented informed consent for adults and minors (Arts. 24 and 31); protection of the profession and the prohibition of teaching professional instruments to persons outside the profession (Arts. 8 and 21). Legal Psychology (semester 7) is the natural anchor.

R5. Anchor internships to psychological service units

Restructure part of the 22 internship credits as supervised practice within HEI psychological units, using the units being piloted in the partner universities, with structured exposure to screening, individual support, awareness activities and crisis protocols. The operational guidelines of these units should be modelled on the "WhatsApp e oltre" format analysed in Section 4.4: free and low-threshold access; a bounded pathway of a small number of sessions, explicitly distinguished from psychotherapy; the five explicit objectives of naming distress, recognising critical knots, identifying resources, reducing stigma and improving knowledge of available services; dedicated weekly hours covering not only consultations but liaison, documentation and case re-elaboration; periodic group supervision on complex cases; a documented referral protocol to health services; and a clinical record designed from the outset to produce outcome data (number of sessions, attainment of objectives, referral and its acceptance, drop-out and causes). This simultaneously staffs the units and trains the workforce that Article 10 of Law ZRU-989 requires for the educational system. For the supervised practice itself to certify competence rather than attendance, the restructured internship should additionally specify: the approved placement settings; the qualifications required of supervisors (including, once R12 is implemented, recognition of supervision as an advanced professional function); the minimum direct professional activities each trainee must perform; a component of direct observation of the trainee's work; documented case discussion; and a final fitness-to-practise assessment by qualified psychologists, so that readiness for independent practice is verified rather than presumed from accumulated hours.

R6. Establish a digital train-the-trainer programme for psychology professors

A digital, replicable train-the-trainer pathway on AI and digital psychology for professors of psychology, producing open educational resources reusable across the 222 Uzbek HEIs. This is the enabling precondition of R1–R3: the EduCATIA data show that only 32.6% of psychology teachers have received AI training while 82.6% already use AI. The pathway should be structured on DigCompEdu, use the SELFIE for Teachers self-reflection tool as an entry diagnostic, and issue micro-credentials – the recognition format promoted by the EU 'Apply AI' strategy (2025) for AI-literacy training.

R7. Build the continuous professional development layer

The partner universities should establish a permanent digital platform for the continuous training of psychologists, with structured pathways aligned with scientific standards, individual supervision components, and priority content addressing the competence gaps of the heterogeneous profession (in particular psychodiagnostics for retrained professionals). In parallel, regulatory recommendations should be submitted to the competent authorities to introduce a CPD requirement into the national framework, completing the initial-training regulation of Law ZRU-989. The regulatory proposal should sketch the full architecture of the national system, not only the obligation: a defined multi-year CPD cycle with a minimum quantity of recognised activity; compulsory core learning areas relevant to public protection (professional ethics and legislative change, consent and records, competence boundaries and referral, safeguarding of minors and vulnerable persons, crisis and suicide-risk procedures, evidence-based practice, cultural and linguistic factors, data protection and cybersecurity, responsible use of AI and automated assessment); additional risk-based requirements for specialist and higher-risk activities; accreditation of providers on scientific-quality criteria, with declared conflicts of interest and the exclusion of mere commercial product demonstrations from recognised CPD; periodic revalidation verifying completed CPD, recent professional practice and the absence of unresolved disciplinary measures, with individualised return-to-practice pathways after prolonged absence; and a graduated compliance ladder (remediation period, individual learning plan, temporary restrictions, suspension, disciplinary proceedings) rather than automatic exclusion. The digital platform already proposed above should serve as the delivery, documentation and monitoring infrastructure of this system, with anonymised data on national training needs as a by-product. Implementation should be phased: obligation, platform, provider standards and core topics first; full revalidation and specialist-maintenance requirements in a second stage, with additional support during the first cycle for practitioners who entered through the retraining route.

R8. Promote the valorisation of the degree over the retraining route

Policy advocacy, supported by the evidence of this analysis, for the progressive alignment of access to the profession with the full degree pathway: the one-year, 700-hour retraining course – which omits psychodiagnostics and testing – cannot be considered equivalent to four years and 7,200 hours of dedicated training, and is clearly not sufficient as a general access route. Interim measures should include: mandatory psychodiagnostics content in the retraining curriculum; restriction of retrained professionals' activity in state educational organisations to the same counselling-and-training perimeter already applied to their private practice; and bridging pathways through which retrained professionals can complete the degree.

R9. Extend the psychological-service mandate to higher education

Recommend the extension of the Article 10 model to HEIs, so that psychological services become mandatory at the tertiary level, where the measured need is most acute (21.8% of students at increased suicidal risk; 95.9% of HEIs without services). The modernised degree provides the workforce; the extended mandate provides the demand and the internship infrastructure.

R10. Align the modernisation with the EU cooperation and financing framework

Frame the modernisation within the Erasmus+ CBHE regional priority for Central Asia ("Digital transformation"), the EU Global Gateway cooperation priorities for Uzbekistan, which include digitalisation, and the EU comprehensive approach to mental health (COM(2023) 298), whose three guiding principles – adequate and effective prevention, access to high-quality and affordable mental healthcare and treatment, and reintegration into society – are precisely what a modernised, digitally competent Uzbek psychological profession would deliver, and whose permeability into the Uzbek legal and policy framework is demonstrated point by point in Section 4.6. Anchor the strategy, as set out in Section 4.7, in the EU financing architecture under the Multiannual Financial Framework 2021–2027: present the modernisation as an implementing vehicle of the Multi-annual Indicative Programme 2021–2027 for Uzbekistan – in particular its Priority Area 2 objective on skills development and digital literacy, its commitment to partnerships with European higher education institutions, and its cooperation facility promoting participation in Erasmus+ – and as a soft-infrastructure complement to the Global Gateway digitalisation agenda agreed between the EU and Uzbekistan. Note for the authors: the instrument frequently referred to in project drafts as the "EU Mental Health Directive" is, correctly, the European Commission Communication "A comprehensive approach to mental health" (COM(2023) 298 final, 7 June 2023); it is a policy communication, not a directive, and should be cited as such.

The three recommendations that follow extend the set from the curricular to the professional-system level. They are addressed to the competent national authorities and complete, on the regulatory side, what R1–R10 propose on the educational side; they respond respectively to Gaps 4, 5 and 6.

R11. Establish a unified public-interest governance framework

A common national governance framework should apply to every person authorised to provide psychological assistance, irrespective of the association to which the practitioner belongs. This does not require abolishing the existing public associations or replicating the Italian Order: associations can retain their representative, training and specialist-development functions, while the functions that directly affect public protection are governed by nationally consistent rules. The framework should provide for a unified national register of authorised practitioners (or fully interoperable registers based on common data and verification standards); uniform minimum requirements for authorisation and certification; a single core code of professional ethics binding on all authorised practitioners; common definitions of professional misconduct with a proportionate national system of sanctions; minimum procedural guarantees on complaints, investigations, hearings, conflicts of interest, reasoned decisions and appeals; structured cooperation and information exchange between associations and public authorities; and publication of anonymised disciplinary decisions and interpretative guidance. Definition of these common standards should rest with, or be formally supervised by, a competent public authority, with structured participation of the associations, universities, service providers and service-user representatives. Implementation can be phased – register, minimum certification criteria and common code first; harmonised disciplinary procedures and a central complaints and appeals mechanism second; only later an assessment of whether a single statutory body is necessary. The objective is regulatory consistency, not institutional uniformity.

R12. Introduce a tiered, activity-based scope-of-practice framework with specialist pathways

The current assumption of broad functional equivalence across access routes and settings should be replaced by a tiered framework in which professional responsibilities are proportionate to verified preparation. Its cornerstone is a national catalogue of professional activities – from supportive and psychoeducational work, through counselling and training, to psychological examination and psychodiagnostic assessment, correction and rehabilitation, interventions involving minors and persons in crisis, and specialist higher-risk practice – each with the qualification, supervised experience and assessment it requires. Two principles govern the catalogue. First, the qualification attaches to the activity performed, not to the employing institution: the same activity requires the same minimum qualification in private practice, state bodies, schools and any other setting, which removes the public/private asymmetry identified in Gap 1 and aligns with the interim measures of R8 (whose bridging pathways and retraining-perimeter restrictions remain the transitional instrument for existing practitioners, together with time-limited, transparently recorded grandfathering accompanied by supervision and restrictions on higher-risk activities). Second, regulation is proportionate to risk: specialist certification is required where the practitioner independently performs diagnosis, treatment, rehabilitation, crisis intervention, forensic evaluation or other activities significantly affecting health, rights, education, employment or legal position – not for every form of institutional work. On this basis, specialist pathways should be sequenced: first psychotherapy – expressly distinguished from counselling and psychocorrection, with a protected title, dedicated postgraduate training, substantial supervised clinical practice and final assessment – together with work with vulnerable populations and high-risk settings, and professional supervision, recognised as an advanced function with national requirements on experience, competence and supervision training; then, in a second stage, proportionate pathways for child and adolescent, educational, work and organisational, forensic, emergency and trauma, military and sport psychology. Specialist qualifications, authorised areas of practice and any conditions or limitations should be recorded in the public register, and titles should accurately reflect recognised qualifications – experience, employment setting or short courses should not confer implied specialist status.

R13. Adopt national standards on consent, minors, confidentiality, records and third-party commissioning

The principles of Articles 8, 10 and 17 of Law ZRU-989 should be translated into operational national standards, applicable to public and private services and to in-person and digital delivery alike, developed by the Ministry of Health with educational authorities, professional associations, universities, child-protection bodies, data-protection experts and service-user representatives. The standards should establish: informed consent as an ongoing process – covering nature and objectives, methods and instruments, the practitioner's qualification, foreseeable benefits and risks, alternatives, confidentiality rules and their legal exceptions, the use of records and data, any involvement of third parties or AI-supported tools, and the right to withdraw – renewed when objectives, methods or data-processing change; for minors, the distinction between the legal consent of representatives, the child's own assent given increasing weight with age and maturity, and the psychologist's independent duty to the child's best interests, with advance clarity for both the minor and the representatives on what will remain confidential, what may be shared and when disclosure is required to prevent serious harm – including the ability to conduct an initial protective assessment of a minor who independently seeks help about violence, abuse or self-harm without automatic disclosure to the alleged source of harm; an interpretation of Article 10 under which institutions and representatives receive functional information necessary to support the learner – never complete session notes, verbatim statements, raw test data or speculative diagnostic impressions; an explicit minimum-necessary disclosure principle, so that a lawful request never automatically justifies disclosure of the entire record; a procedure for investigative and judicial requests under Article 17 – verification of the legal basis, scope and proportionality, the possibility of seeking review of uncertain requests, differential treatment of administrative facts, professional conclusions, clinical records, raw psychometric data and third-party information, and documentation of every disclosure; minimum content, secure storage, access, correction, transfer and destruction rules for professional records, with a national minimum retention period; security requirements for digital communications and remote services (encryption, identity verification, restrictions on recording, storage location, emergency procedures, and the prohibition on entering client-identifiable material into unapproved general-purpose AI systems, consistent with Section 6); a data-breach procedure with containment, assessment, documentation, notification and corrective duties; written clarification, in third-party commissioning, of who the client is, who commissions and pays, what the commissioning party will and will not receive, and how conflicts between individual and institutional interests are managed – with no undisclosed institutional access to confidential content; and a genuine-anonymisation standard for the training and quality-improvement use permitted by Article 17, assessing re-identification risk beyond the mere removal of names. Implementation should include model consent and information forms, dedicated guidance for schools and universities, disclosure decision trees, safeguarding protocols and compulsory professional training – content that maps directly onto the R4 module and the institutional protocol of Section 6.2.

At least twenty of the sources cited in this document originate from the authors' own analysis and network (needs analysis, national assessments, legal analysis, sector reports); the reference list below consolidates them with the European regulatory and scientific sources.

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Curriculum Analysis and recommendations for Bachelor's Degree Program: 6B04102 IT Entrepreneurship, Astana IT University

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Program Passport & General Information

Parameter	Specification
Program Code & Title	6B04102 IT Entrepreneurship
Field of Education	6B04 Business, Administration and Law
Training Area	B044 Management and Administration
Group of Educational Programs	6B041 Business and Administration
NQF / EQF Level	Level 6
Duration of Study	3 Years
Total Credits	240 ECTS / Academic Credits
Application Area	Designed to train specialists with knowledge in entrepreneurship, management, information technology, economics, marketing, and finance.
Professional Standards Reference	• Risk Management of an Innovative Project (Atameken Annex No. 13) • Commercialization of an Innovative Project (Atameken Annex No. 3) • Development and Transformation of Innovative Ideas (Atameken Annex No. 9) • Support of an Innovative Project (Atameken Annex No. 11)

Program Objective & Concept

Objective of EP: Training of highly qualified specialists and product managers with entrepreneurial skills capable of effectively solving applied economic problems and developing IT business infrastructure.

Brief Concept: Focused on leadership, personnel management, motivation, decision-making, communication, conflict management, group dynamics, and organizational change with practical application to enhance organizational efficiency.

Graduate Profile & Career Prospects

- **Awarded Degree:** Bachelor of Business and Management in "6B04102 IT Entrepreneurship"
- **Career Roles:** Entrepreneur, Project Manager, Businessman, Product Manager, Marketer, Business Analyst, Online Sales Manager, Personal Brand Manager, Front-End Developer, System Administrator/Analyst.
- **Atlas of New Professions Roles:** Product Manager, MVP Manager, R&D Manager.

The Bachelor's programme in IT Entrepreneurship already contains a comparatively strong technical and business foundation for the responsible use of artificial intelligence. Its documented curriculum includes Python programming, machine learning for business applications, data mining, database management, IT risk management, information security, Agile management, IT governance, business models, intellectual property, and technological entrepreneurship. We believe that for a B.A. studies there should set up more fundamentals in Mathematics, Statistics, basic understanding of economics as well as business hard skills like controlling strategic planning etc.

All these subjects could be effectively taught with AI blended learning concepts.

Strengths of the program

Interdisciplinary Orientation The programme combines business, organisational, and technological perspectives. This combination is particularly relevant for digital transformation, platform-based business, start-ups, and technology-oriented enterprises.

Applied Data and AI Competences Python, machine learning, data mining, and database management provide useful capabilities for data-driven decision-making and digital business models.

Entrepreneurship Focus Modules concerning business models, intellectual property, technological entrepreneurship, and commercialisation support the development and market introduction of innovative products.

Relevant Management Competences Leadership, teamwork, conflict management, project organisation, and change management are meaningfully integrated and correspond to the demands of product and project management roles. Governance, Risk, and Security Coverage IT Risk Management, Information Security Fundamentals, and IT Governance and Audit extend the programme beyond basic technology and entrepreneurship content. These elements are valuable for responsible digital innovation and organisational decision-making.

Already implemented AI-related curriculum provision

Module	Credits	Documented content	AI relevance
Introduction to Programming (Python)	5	Data structures, functions, modules, and classes in Python for applied tasks	Technical foundation for data processing, automation, and AI workflows
Machine Learning for Business Applications	5	Supervised and unsupervised learning for segmentation, sales forecasting, and fraud detection	Direct AI and predictive-analytics provision

Data Mining for Business Decisions	5	Classification, clustering, predictive modelling, and extracting insights from big data	Direct data and AI application provision

Database Management Systems	5	Conceptual data modelling through physical implementation	Data architecture, data quality, and provenance foundation
IT Risk Management	5	Identification, assessment, qualitative/quantitative analysis, and response strategies	Relevant basis for AI risk management
Information Security Fundamentals	5	Security concepts, protocols, threat modelling, and professional tools	Relevant basis for AI security and privacy
Business Model & Intellectual Property	5	Business models, monetisation, and IP protection law	Relevant to AI business models, copyright, and ownership
Technological Entrepreneurship	5	Start-up development, patents, strategy, and Kazakhstan IP legislation	Relevant to responsible AI venture creation
Agile Management in Virtual Environments	5	Agile/Scrum methods and project-automation tools	Relevant to AI-enabled product development and collaborative workflows
IT Governance and Audit	5	Enterprise IT management, compliance auditing, COBIT, and IT maturity	Strong foundation for AI governance and assurance

Expanded the AI Competence Framework

Competence domains

AI competence domain	Expected graduate capability
Understanding AI	Explain key distinctions among automation, machine learning, generative AI, predictive analytics, and AI-enabled decision support; identify limitations and failure modes
Operational AI use	Select appropriate AI tools; use prompt engineering, iterative prompting, multimodal interaction, workflow design, comparison of tools, and documentation of use
Critical evaluation	Verify AI outputs; detect factual error, hallucination, bias, unsupported claims, weak evidence, and misleading business recommendations
Data, privacy, and security	Apply data minimisation, confidentiality, data-quality assessment, provenance checks, secure tool selection, and appropriate handling of stakeholder data
Ethics, integrity, copyright, and fairness	Declare AI use; respect authorship, IP, copyright, academic integrity, fairness, and responsible innovation principles
Human responsibility and oversight	Retain human judgement; justify acceptance, revision, or rejection of AI recommendations; identify high-risk decisions requiring supervision
Inclusion and accessibility	Use AI to improve accessibility and multilingual communication; identify discriminatory, linguistic, functional, socioeconomic, and usability barriers
Professional entrepreneurship application	Design, evaluate, govern, and communicate AI-enabled products, business models, customer insights, risk controls, and innovation strategies

Expanded operational AI skills

Operational competence should extend beyond basic use of chatbots. By graduation, students should be able to:

- define a business or product problem before selecting an AI tool;
- compare tools based on purpose, reliability, data handling, accessibility, cost, and organisational fit;
- write clear, context-specific prompts;
- improve outputs through iterative prompting and structured critique;

- use multimodal interaction where appropriate, including text, data tables, images, diagrams, audio, and code;
- validate AI-generated analysis against credible sources, datasets, and disciplinary knowledge;
- document tools, prompts, data inputs, outputs, edits, verification actions, and human decisions;
- distinguish brainstorming support from delegated judgement;
- disclose material AI contribution in academic and professional work;
- design AI-supported workflows that preserve human accountability.

AI Curriculum Maturity Assessment

Proficiency levels

0 — Not evidenced	No reliable documentation is available
1 — Initial	Isolated activities or general references; no coherent framework
2 — Developing	Some relevant modules, practices, or resources; limited integration
3 — Defined	Programme-wide expectations, policies, roles, and assessment processes are documented
4 — Managed	Implementation is monitored through evidence, staff development, quality assurance, and periodic review
5 — Optimising	Continuous improvement, innovation, external engagement, and systematic evaluation are embedded

Domain	Maturity	Evidence / Rationale
AI curriculum content	Developing	ML, data mining, Python, databases, and IT governance are explicitly present
Operational generative-AI competence	Initial	Prompting, iterative use, multimodal interaction, and tool comparison are not evidenced
Critical AI literacy	Initial	Critical analysis is stated generally, but AI-output verification, bias, hallucination, and uncertainty are not explicit

AI ethics and integrity	Initial	General social-ethical values and IP are present, but AI-specific ethics, disclosure, and integrity procedures are not evidenced
Privacy, security, and data governance	Developing	Security, risk, database, and governance modules provide a foundation; AI-specific data governance is not evidenced
AI governance and compliance	Developing	IT governance, audit, risk management, and IP content exist; AI-specific governance, procurement, lifecycle controls, and regulation are not evidenced
Accessibility and inclusion	Initial	Bilingual communication and general social values are documented; accessibility and inclusive AI design are not
Assessment in AI-rich environments	Not evidenced	No assessment rules, rubrics, AI-use declarations, or process evidence are supplied

Overview

Across the eight AI-competence domains assessed, the curriculum shows a consistent two-tier pattern: technical infrastructure is comparatively mature, while the human, ethical, and evaluative dimensions of AI use remain underdeveloped. Of eight domains, three are rated "Developing," four "Initial," and one "Not evidenced." No domain reaches full maturity.

Where the curriculum is strongest

The three "Developing" domains — AI Curriculum Content, Privacy/Security/Data Governance, and AI Governance & Compliance — rest on the same foundation: existing technical and managerial disciplines (Python, databases, data mining, machine learning, IT risk, audit, and IP law). In every case, maturity is capped because the content is general-purpose rather than AI-specific: security and governance frameworks exist, but none are adapted to AI systems' particular risks (model risk, data provenance, algorithmic auditability, AI procurement).

Where the curriculum is weakest

The four "Initial" domains — Operational Generative-AI Competence, Critical AI Literacy, AI Ethics and Integrity, and Accessibility/Inclusion — share a common cause: the curriculum states adjacent general competences (critical thinking, social-ethical values, communication skills) without operationalising them for AI. Students are not evidenced to practice prompting, compare tools, verify outputs, detect bias or hallucination, declare AI use, or apply inclusive AI design. The ethical and cognitive scaffolding exists; it has simply not been extended to AI-specific practice.

Critical gap

Assessment in AI-Rich Environments is the only domain rated "Not evidenced." Implementing AI is always related to generate an environment to support technical development. In the curriculums it is not evidenced that there are any crosssubject activities.

AI Curriculum Gap Analysis

Twelve gaps were identified between the AI competences the programme should develop, the competences documented in the curriculum, and the competences that can currently be verified through assessment. Priority reflects professional relevance, risk exposure, and the strength of available evidence; it does not by itself determine the order of implementation, which should also account for feasibility and available resources. The gaps are presented below in narrative form, beginning with those rated critical and followed by those rated high.

Gaps rated critical

GAP-01, the absence and progression gap, concerns the lack of an explicit, progressive programme-wide AI competence framework that moves students from a foundation level through to an advanced level. Without such a framework, isolated technical modules cannot substitute for a coherent, developmental pathway of AI competence across the degree.

GAP-03, the critical-evaluation gap, reflects the absence of explicit learning outcomes or assessment activities directed at the verification of AI outputs. The curriculum does not document how students are expected to detect hallucinations, identify bias, judge uncertainty, or challenge unsupported claims produced by AI systems, even though these skills are essential to responsible professional use.

GAP-05, the governance gap, arises because no programme-wide AI governance framework is documented. This includes the absence of defined policy, roles, procurement practices, approved-tool lists, copyright treatment, data-governance rules, lifecycle-risk management, and monitoring of applicable regulation. This gap is discussed in more detail below.

GAP-06, the privacy and security gap, is notable because general security content does exist within the curriculum, yet it does not extend to AI-specific practice. There is no explicit treatment of data classification for AI use, data minimisation, restrictions on entering confidential data into AI tools, or guidance on selecting tools with adequate security safeguards.

GAP-07, the ethics, fairness, and integrity gap, follows a similar pattern. General ethical values and intellectual-property content are present in the programme, but they have not been extended to AI-specific concerns such as fairness, bias, transparency, academic integrity in AI-assisted work, or requirements to disclose AI use.

GAP-10, the assessment gap, is one of the most consequential findings. Assessment modes and rules governing the use of AI in assessed work are not documented anywhere in the curriculum. As a result, authentic evidence of student competence, including AI-related competence, cannot currently be confirmed.

Gaps rated high

GAP-02, the explicitness and implementation gap, recognises that AI-related content is present through machine-learning and data-mining modules, but that generative AI, prompt engineering, tool selection, multimodal interaction, and iterative prompting are not made explicit within these or other modules. The underlying technical foundation exists, but it has not been extended to cover how students should work with generative AI tools in practice.

GAP-04, the AI collaboration gap, concerns the absence of documented requirements for students to record the prompts, tools, outputs, revisions, and verification steps involved in AI-supported work, or to clearly identify their own human contribution. This gap is discussed in more detail below.

GAP-08, the human oversight gap, exists despite the presence of governance and risk-management foundations elsewhere in the programme. There are no explicit protocols describing how students or staff should exercise oversight of AI-generated recommendations, nor any requirement to justify why an AI recommendation was accepted or rejected.

GAP-09, the accessibility and inclusion gap, reflects the absence of documented content on AI accessibility, multilingual inclusion, disability inclusion, or the discriminatory impact that AI systems can have on different groups of students or users.

GAP-11, the staff-capacity gap, indicates that no evidence was found of staff development aligned with AI pedagogy, AI-related assessment design, AI governance, privacy practice, accessibility, or discipline-specific AI application. Without capable staff, curricular improvements in the other domains are unlikely to be implemented effectively.

GAP-12, the infrastructure gap, concerns the absence of evidence relating to approved AI tools, licences, secure technical environments, accessible alternatives for students with different needs, technical support arrangements, and equitable access across the student body.

AI Governance Gap

The programme has a valuable foundation in IT governance, audit, risk management, information security, intellectual property, and technological entrepreneurship. Nevertheless, an AI governance gap remains, because the available documents do not show explicit coverage of institutional policy governing student and staff AI use, nor of the permitted, restricted, and prohibited uses of AI tools. There is no documented approach to data classification or to rules governing the upload of personal, confidential, customer, employee, financial, or proprietary data into AI systems. Similarly, the documentation does not address approved tools, vendor assessment, procurement, contracts, licensing, or retention arrangements, nor the treatment of copyright and ownership over AI-assisted outputs.

Beyond these procedural elements, the programme does not evidence documentation and transparency requirements for AI use, nor clearly assigned responsibilities for human oversight and escalation when AI-supported decisions are questioned. There is no visible framework for AI-system lifecycle governance, ongoing monitoring, or incident reporting, and no mechanism ensuring that AI-supported decisions remain auditable after the fact. Finally, the curriculum does not show any process for monitoring relevant legal and regulatory developments, including AI-related regulation that may become applicable to the institution's operating context. Taken together, these omissions mean that governance of AI use currently depends on individual initiative rather than on an institutionally defined framework.

AI Collaboration Gap

The programme prepares students for teamwork and Agile project management, but the documentation does not show how human-AI co-creation should be managed within that collaborative context. In particular, there is no explicit treatment of collaborative prompting

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within teams, nor guidance on how human roles should be allocated once AI tools are introduced into a team's workflow. The curriculum does not describe how individual and team contributions should be clearly attributed when AI tools have participated in producing a piece of work.

The gap also extends to record-keeping and communication. There is no documented expectation that students maintain logs of prompts, outputs, revisions, and decisions made during AI-supported work, nor any requirement to explain where AI was used and where human judgement ultimately prevailed. Peer review of AI-supported work is not addressed, and the curriculum does not evidence any explicit competence in communicating uncertainty and limitations to clients, investors, managers, and other stakeholders who may rely on AI-supported outputs produced by students. As with the governance gap, these omissions mean that collaborative AI practice, where it occurs, is not currently guided or verified by any documented curricular provision.

Matching Dublin Descriptors learning outcomes for Bachelors

The Dublin Descriptors and DigComp operate on two different axes. The Dublin Descriptors are the generic, discipline-independent descriptors adopted under the Bologna Process (Qualifications Framework for the European Higher Education Area) to describe what *any* graduate of a given cycle — short cycle, Bachelor, Master, Doctorate — should be able to do, regardless of subject. There are five: Knowledge and Understanding, Applying Knowledge and Understanding, Making Judgements, Communication, and Learning Skills. They say nothing about digital technology specifically; they describe the cognitive and professional maturity expected at a degree level. A Bachelor's-level "Making Judgements" descriptor, for instance, expects a graduate to gather and interpret relevant data to form judgements that include reflection on social, scientific or ethical issues — whether that data comes from a lab experiment, a business case, or an AI model output is irrelevant to the descriptor itself.

DigComp — the domain-competence axis

DigComp (the Digital Competence Framework for Citizens) is the opposite kind of framework: it is domain-specific rather than degree-generic. It defines 21 competences across five areas — Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, and Problem Solving — and grades proficiency on an 8-level scale from foundation to highly specialised, based on task complexity, autonomy, and cognitive domain. DigComp says nothing about qualification cycles; it describes what "being digitally competent" looks like at any age or educational level, from basic citizen literacy to expert practice.

How they relate

The two frameworks are complementary rather than overlapping: Dublin tells you *how sophisticated* a competence must be for a given degree level; DigComp tells you *which digital competence* is being exercised. In practice, every DigComp competence can be expressed at any of the five Dublin levels. Take "evaluating the quality and provenance of data" (DigComp: Information and Data Literacy): at a foundation level this might just mean recognising that a source exists; at Dublin's "Making Judgements" level for a Bachelor's graduate, it means independently judging data representativeness, bias, and business consequences well enough to justify accepting, revising, or escalating an AI-generated output.

This is exactly the logic used in the recommendations you shared: each learning outcome carries a DigComp tag (e.g., "Safety," "Problem Solving," "Information and Data Literacy") to specify *what kind* of digital competence is being built, and a Dublin-Descriptor mapping to specify *what level of cognitive/professional maturity* a graduating IT-Entrepreneurship student must reach with that competence. Used together, they let a programme demonstrate two things simultaneously: that its AI-related content covers the right digital-competence areas (DigComp), and that it does so at a standard appropriate to a Bachelor's degree rather than merely at a basic-user level (Dublin).

One practical consequence for curriculum design: a gap can exist in either dimension independently. A module might cover the right DigComp area (e.g., data literacy) but only at a foundation proficiency inappropriate for a graduating cohort — a *Dublin-level* gap — or it might sit at the right cognitive level but neglect a DigComp area altogether (e.g., no Safety-related content on data protection) — a *DigComp-coverage* gap. Several of the gaps identified in the AI curriculum analysis (e.g., GAP-03 critical evaluation, GAP-06 privacy/security) are best read this way: not just "missing content" but content missing at the specific DigComp area *and* Dublin level a Bachelor's graduate needs.

Dublin Descriptors Alignment

AI-Related Learning Outcomes — Recommendations

The analyzed Programe and DigComp-aligned learning outcomes proposed are now matched below according to the five Dublin Descriptors:

Knowledge and Understanding, Applying Knowledge and Understanding, Making Judgements, Communication, and Learning Skills. This restructuring is intended to show that the proposed AI-related competences taken together, address the full range of generic degree-level outcomes expected of a bachelor's graduate, rather than only technical or procedural skill.

Knowledge and Understanding

Graduates are expected to explain the differences among automation, machine learning, predictive analytics, and generative AI, including their principal limitations, as a foundational outcome underpinning all subsequent AI-related work. Within the revised Machine Learning and Data Mining modules, this knowledge extends to understanding the quality, provenance, and representativeness of data used in business machine-learning tasks, and to recognising the causes of bias, overfitting, data leakage, and misleading performance claims. The proposed AI-governance component further requires graduates to understand governance structures, responsibilities, and accountability arrangements, procurement and vendor due-diligence practice, the distinction between approved and prohibited tools, data governance and retention principles, copyright and licensing treatment of AI-assisted outputs, and the legal and regulatory obligations relevant to the institution's operating environment. Together, these outcomes establish the conceptual and factual basis on which application, judgement, and communication depend.

Applying Knowledge and Understanding

Graduates are expected to apply approved AI tools to defined entrepreneurship and business-analysis tasks, using documented prompts and iterative refinement, and to design an AI-supported workflow for a discipline-specific business or product-management task that incorporates privacy, accessibility, documentation, and human oversight. This applied competence is developed further through the construction and refinement of prompts to generate, compare, and improve business artefacts such as customer personas, value propositions, market-research questions, user stories, project-risk registers, and product documentation, and through the practical use of task definition, prompt engineering, iterative prompting, structured prompts, and multimodal interaction where relevant. In the governance domain, application takes the form of conducting a risk and governance assessment for an AI-enabled product, business process, or start-up use case, and of developing a corresponding AI governance plan specifying purpose, data categories, roles, vendor and tool criteria, human oversight, privacy controls, documentation, and accessibility measures. Applied competence also extends to designing AI-supported customer or user interactions that incorporate accessibility and multilingual communication considerations.

Making Judgements

A substantial share of the proposed outcomes concerns the exercise of judgement rather than technical execution alone. Graduates are expected to analyse AI-generated outputs for reliability, relevance, data quality, bias, and uncertainty, and to evaluate whether AI-generated recommendations should be accepted, revised, rejected, or escalated for human review. Within the Machine Learning and Data Mining modules, this includes identifying and justifying mitigation measures for bias, discriminatory impact, overfitting, leakage, or misleading performance claims, and comparing a business decision made with and without AI support in order to justify the appropriate level of human oversight. Judgement is also central to the governance strand, where graduates must justify the acceptance, modification, suspension, or rejection of an AI use case on the basis of risk, fairness, legality, business value, and professional responsibility, and must audit a simulated AI-enabled process for transparency, security, data-governance, and accountability weaknesses. In the domain of accessibility and inclusion, graduates are expected to assess AI-enabled digital products or workflows for accessibility barriers affecting users with different linguistic, cognitive, sensory, physical, digital-literacy, or socioeconomic profiles, and to evaluate the potential discriminatory impact of automated segmentation, profiling, recommendation, recruitment, pricing, or fraud-detection decisions. Evaluating whether a specific AI tool is appropriate to a business task, using criteria of quality, privacy, accessibility, cost, explainability, and organisational risk, extends this judgement-oriented competence into tool selection itself.

Communication

Several proposed outcomes and assessment forms require graduates to communicate AI-related reasoning to varied audiences. Graduates must interpret model outputs and communicate uncertainty, false positives, false negatives, and potential business consequences arising from a model, and must document a human-AI collaborative workflow in a way that makes the tools used, prompt versions, source material, verification procedures, revisions, and final human decisions transparent to others. Assessment evidence associated with these outcomes includes an oral explanation of a model's limitations, a decision memo specifying when human approval is required, viva voce or oral defence of AI-supported work, and a board-style presentation and defence of an AI governance dossier. Collaborative prompting within teams and the explicit statement of human and AI contribution likewise depend on clear communication among team members, while the assessment principles proposed for AI-rich learning require students to declare material AI use and to provide process evidence of their own reasoning, which is itself a communicative act directed at the assessor.

Learning Skills

The proposed outcomes also cultivate the self-directed learning skills expected of a Dublin-Descriptor-aligned graduate, particularly the capacity to reflect on one's own use of AI and to continue developing competence beyond the immediate task. Reflective commentary on risk, privacy, bias, accessibility, and human oversight is required as part of the overall assessment evidence, and the AI-use and verification portfolio and prompt/output/revision log are designed to make a student's evolving practice visible over time rather than only at a single point of assessment. Peer assessment of collaboration and attribution within team projects extends this reflective capacity to the evaluation of others' contributions as well as one's own. The accessibility strand includes a fairness-impact reflection and a usability review with documented mitigation actions, reinforcing the habit of revisiting and improving one's own work in light of new evidence. Finally, the programme-wide assessment principles proposed for AI-rich learning environments — requiring process evidence rather than only final outputs, and assessing verification, judgement, and revision rather than rewarding uncritical generation — are themselves intended to instill a disposition toward continuous critical learning that graduates can apply independently after completing the programme.

Modernisation recommendations

Learning Outcomes Aligned with Dublin Descriptors

The following recommendations use the five Dublin Descriptors for Bachelor-level higher education:

1. **Knowledge and Understanding**
2. **Applying Knowledge and Understanding**
3. **Making Judgements**
4. **Communication**
5. **Learning Skills**

Recommendation ENT-AI-R01

Recommendation	Details
Code and title	ENT-AI-R01 — Introduce programme-wide AI competence progression
Identified gap	GAP-01, GAP-02, GAP-03, GAP-04, GAP-07, GAP-08, GAP-09

Intended competence	Students progressively develop Foundation, Intermediate, and Advanced competence in responsible, critical, accessible, and professionally applied AI use.
Target group	All students, from Year 1 to Year 3.
Proposed intervention	Introduce a distributed programme-wide AI competence strand rather than a stand-alone introductory tool course.
Assessment evidence	Short supervised foundational assessment; AI use and verification portfolio; prompt/output/revision log; oral defence of an AI-supported business decision; team project with documented individual contribution; reflective commentary on risk, privacy, bias, accessibility, and human oversight.
Responsible unit	Programme leadership with module coordinators for Python, Machine Learning, Data Mining, IT Risk, Information Security, Business Model & IP, Technological Entrepreneurship, Agile Management, and IT Governance.
Timeframe	Short term: design during the next curriculum review cycle; phased implementation over one academic year.

Suggested Progression for ENT-AI-R01

Stage	Target level	Main focus
Year 1	Foundation	AI concepts, limitations, basic data literacy, introduction to responsible tool use, privacy basics, academic integrity, accessible and multilingual use
Year 2	Intermediate	Prompt engineering, iterative prompting, tool comparison, output verification, bias detection, documented AI-supported analytics, secure data handling
Year 3	Advanced	AI-supported product and business workflow design, governance, human oversight, risk assessment, ethics, accessibility, stakeholder communication, authentic project application

Learning Outcomes for ENT-AI-R01 Aligned with Dublin Descriptors

Dublin Descriptor	Learning outcome
Knowledge and Understanding	Explain the differences among automation, machine learning, predictive analytics, and generative AI, including their main capabilities, limitations, risks, and appropriate business applications.
Applying Knowledge and Understanding	Apply approved AI tools to defined entrepreneurship and business-analysis tasks using documented prompts, iterative refinement, verification procedures, and appropriate data-handling practices.
Making Judgements	Critically evaluate the reliability, relevance, data quality, bias, uncertainty, accessibility implications, and ethical risks of AI-generated outputs; justify whether recommendations should be accepted, revised, rejected, or escalated for human review.
Communication	Communicate and document AI-supported work clearly by recording the tool used, prompts, inputs, outputs, revisions, verification actions, limitations, human contribution, and AI contribution.
Learning Skills	Independently identify emerging AI tools and practices relevant to entrepreneurship and product management, select appropriate learning resources, and update personal practice in response to technological, professional, legal, and ethical developments.

Recommendation ENT-AI-R02

Recommendation	Details
Code and title	ENT-AI-R02 — Revise Machine Learning and Data Mining modules for critical AI literacy
Identified gap	GAP-03, GAP-07, GAP-08
Relevant modules	Machine Learning for Business Applications; Data Mining for Business Decisions
Proposed intervention	Add explicit learning outcomes and assessed activities on verification, bias, uncertainty, fairness, data representativeness, and limitations of business predictions.
Teaching activities	Customer-segmentation case with representativeness issues; sales-forecasting case with changing market conditions; fraud-detection case addressing false positives and customer harm; structured exercise in identifying misleading AI-generated claims; comparison of human judgement, statistical analysis, and AI-supported recommendation.
Assessment	Critical model card or business-AI impact statement; data-quality and bias audit; oral explanation of a model’s limitations; decision memo specifying when human approval is required.
DigComp alignment	Information and Data Literacy; Safety; Problem Solving

Target level	Intermediate progressing to Advanced

Learning Outcomes for ENT-AI-R02 Aligned with Dublin Descriptors

Dublin Descriptor	**Learning outcome**
Knowledge and Understanding	Explain how data quality, provenance, representativeness, model design, performance measures, and contextual conditions influence the reliability of business machine-learning and data-mining outputs.
Applying Knowledge and Understanding	Apply data-quality checks, model-performance interpretation, and documentation methods to a business machine-learning or predictive-analytics task.
Making Judgements	Evaluate the risks of bias, discriminatory impact, overfitting, data leakage, false positives, false negatives, and misleading performance claims; justify proportionate mitigation measures and the required degree of human oversight.
Communication	Communicate model limitations, uncertainty, potential business consequences, and conditions for safe use to technical and non-technical stakeholders through a model card, business-AI impact statement, or decision memo.
Learning Skills	Independently develop and update methods for checking data, testing assumptions, interpreting model results, and monitoring changes in business conditions that may affect model validity.

Recommendation ENT-AI-R03

Recommendation	**Details**
Code and title	ENT-AI-R03 — Integrate operational generative-AI and human-AI collaboration skills
Identified gap	GAP-02 and GAP-04
Relevant modules	Introduction to Programming (Python); Agile Management in Virtual Environments; Business Model & Intellectual Property; Technological Entrepreneurship
Proposed intervention	Embed practical and documented use of generative-AI tools into authentic entrepreneurship and product-management workflows.
Required skills	Task definition before tool selection; prompt engineering; iterative prompting; use of structured prompts and evaluation criteria; multimodal interaction when relevant; comparison of at least two appropriate tools or methods; documentation of tools, prompts, inputs, outputs, edits, and verification; collaborative prompting and

	allocation of roles in teams; explicit statement of human contribution and AI contribution.
Assessment	AI collaboration portfolio; prompt iteration log; team workflow charter; peer assessment of collaboration and attribution; viva voce or oral defence.
DigComp alignment	Digital Content Creation; Communication and Collaboration; Problem Solving
Target level	Intermediate

Learning Outcomes for ENT-AI-R03 Aligned with Dublin Descriptors

Dublin Descriptor	Learning outcome
Knowledge and Understanding	Explain the principles of task definition, tool selection, prompt engineering, iterative prompting, multimodal interaction, collaborative prompting, and documentation of human-AI collaboration.
Applying Knowledge and Understanding	Construct and refine prompts to generate, compare, and improve business artefacts, including customer personas, value propositions, market-research questions, user stories, project-risk registers, and product documentation.
Making Judgements	Evaluate whether an AI tool is appropriate for a specific business task using criteria of output quality, reliability, privacy, accessibility, cost, explainability, intellectual-property implications, and organisational risk.
Communication	Document a human-AI collaborative workflow, including tools used, prompt versions, source materials, inputs, outputs, verification procedures, revisions, team roles, and final human decisions.
Learning Skills	Independently experiment with and compare appropriate AI tools and prompting strategies, using evidence from reflection and evaluation to improve future business and product-management workflows.

Recommendation ENT-AI-R04

Recommendation	Details
Code and title	ENT-AI-R04 — Establish AI governance and responsible innovation within existing governance modules
Identified gap	GAP-05, GAP-06, GAP-07, GAP-08

Relevant modules	IT Governance and Audit; IT Risk Management; Information Security Fundamentals; Business Model & Intellectual Property; Technological Entrepreneurship
Proposed intervention	Create a coherent AI-governance component distributed across the listed modules.
Core content	AI governance structures, responsibilities, and accountability; risk-based evaluation of AI use cases; procurement and vendor due diligence; approved versus prohibited tools; data governance, data minimisation, retention, and access control; copyright, IP, licensing, and ownership of AI-assisted outputs; transparency and documentation; human oversight, escalation, incident reporting, and audit trails; accessibility, non-discrimination, and stakeholder impact; monitoring of relevant legal and regulatory obligations in the operating environment.
Assessment	AI governance dossier; AI impact and risk assessment; procurement/vendor evaluation simulation; audit report; board-style presentation and defence.
DigComp alignment	Safety; Problem Solving; Information and Data Literacy; Digital Content Creation
Target level	Advanced by graduation

Learning Outcomes for ENT-AI-R04 Aligned with Dublin Descriptors

Dublin Descriptor		Learning outcome
Knowledge and Understanding		Explain the purpose and components of AI governance, including accountability, risk-based management, procurement, vendor due diligence, data governance, copyright, licensing, transparency, accessibility, non-discrimination, human oversight, and auditability.
Applying Knowledge and Understanding		Conduct a risk and governance assessment for an AI-enabled product, business process, or start-up use case and develop an AI governance plan appropriate to the context.
Making Judgements		Justify the acceptance, modification, suspension, or rejection of an AI use case on the basis of risk, fairness, legality, privacy, security, accessibility, business value, and professional responsibility.
Communication		Present AI governance requirements, impact findings, risk controls, oversight arrangements, and escalation procedures in a clear governance dossier, audit report, procurement evaluation, and board-style presentation.
Learning Skills		Independently monitor and interpret relevant changes in AI technologies, organisational requirements, professional

		standards, and the legal or regulatory environment affecting AI-enabled ventures.

Recommendation ENT-AI-R05

Recommendation	**Details**
Code and title	ENT-AI-R05 — Embed accessibility, multilingual inclusion, and fairness
Identified gap	GAP-09
Relevant modules	Agile Management in Virtual Environments; Human-Computer Interaction content under ON 9; Business Model & Intellectual Property; Technological Entrepreneurship; Machine Learning
Proposed intervention	Introduce accessible and inclusive AI design requirements in projects and business cases.
Assessment	Accessibility and inclusion checklist within product documentation; inclusive user-persona analysis; fairness impact reflection; usability review with documented mitigation actions.
DigComp alignment	Communication and Collaboration; Safety; Problem Solving
Target level	Intermediate to Advanced

Learning Outcomes for ENT-AI-R05 Aligned with Dublin Descriptors

Dublin Descriptor	**Learning outcome**
Knowledge and Understanding	Explain how AI-enabled products and workflows can create or reduce barriers for users with different linguistic, cognitive, sensory, physical, digital-literacy, and socioeconomic characteristics.
Applying Knowledge and Understanding	Design an AI-supported customer or user interaction that incorporates accessibility, multilingual communication, inclusive user requirements, and appropriate human support.
Making Judgements	Evaluate potential discriminatory impacts of automated segmentation, profiling, recommendation, recruitment, pricing, or fraud-detection decisions and justify mitigation actions.
Communication	Communicate accessibility, inclusion, and fairness requirements in product documentation, user personas, project specifications, and stakeholder presentations.
Learning Skills	Independently identify user needs, accessibility standards, inclusive-design resources, and emerging fairness risks relevant to AI-enabled entrepreneurship and product management.

Recommendation ENT-AI-R06

Recommendation	Details
Code and title	ENT-AI-R06 — Redesign assessment for AI-rich learning
Identified gap	GAP-10
Proposed intervention	Establish programme-wide assessment principles that distinguish legitimate AI assistance from inappropriate substitution and that require students to demonstrate understanding, judgement, and responsibility.

Assessment Principles for ENT-AI-R06

No.	Assessment principle
1	State whether AI use is permitted, limited, prohibited, or required for each assessment.
2	Require declaration of material AI use.
3	Require process evidence, not only final outputs.
4	Assess verification, judgement, and revision rather than rewarding uncritical generation.
5	Include oral, supervised, staged, or practical components where appropriate.
6	Avoid using automated AI-detection tools as the sole evidence of misconduct.
7	Provide clear procedures for feedback, disputes, and appeals.

Assessment Evidence Linked to Dublin Descriptors

Dublin Descriptor	Suitable assessment evidence
Knowledge and Understanding	Short supervised test; concept explanation; annotated case analysis on AI capabilities, limitations, privacy, ethics, or governance.
Applying Knowledge and Understanding	Practical task using an approved AI tool; documented prompt and workflow log; AI-supported data-analysis or entrepreneurship task.
Making Judgements	Critical evaluation of an AI output; risk and bias audit; decision memo; justification of acceptance, rejection, revision, or escalation for human review.
Communication	Oral defence; viva voce; stakeholder presentation; governance dossier; model card; business-AI impact statement; clear declaration of AI contribution.

Learning Skills	Reflective portfolio; self-evaluation of tool selection and verification strategy; learning plan for emerging tools, policy changes, and professional AI practice.

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Programme level	Bachelor's
Source reviewed	KZ Medical and Preventive Medicine(1).pdf
Document date	2023; Revision 1
Analysis date	30 July 2026

1. Executive summary

The reviewed programme has a substantial disciplinary base for data-informed public-health practice but does not document explicit artificial-intelligence or machine-learning education. The strongest foundations are the required Information and Communication Technologies course (5 ECTS), Biostatistics (5 ECTS), Fundamentals of Scientific Research Methodology (4 ECTS), two Public Health courses, the Epidemiology module, research/project work, and an elective that explicitly combines socio-hygienic monitoring with geoinformation systems and public-health risk assessment. Programme Learning Outcome 5 also requires graduates to interpret scientific research through modern collection, processing and analysis of information on the basis of evidence and bioethics. These components provide viable curricular locations for modernisation without displacing the programme's core professional identity.

The evidence nevertheless remains predominantly statistical, information-system and research-method oriented. No module or learning outcome explicitly names artificial intelligence, machine learning, data mining, automated analysis, generative AI, recommendation systems or algorithmic decision support. There is likewise no explicit provision on validating AI-generated outputs, hallucinations, model interpretation, bias, dataset shift, privacy-preserving data use, transparency, accountability or human oversight. Academic integrity and bioethics are present, but neither is connected in the documentation to AI-assisted study, research or professional decision-making.

Comparison with the EduCATIA questionnaire and focus-group findings confirms that these are not solely documentary gaps. The questionnaire findings describe widespread AI use accompanied by limited advanced self-perceived knowledge, uneven formal training and strong demand for further discipline-specific education, particularly among medical students and students at KazNMU. Teachers expressed substantial concern about the reliability of AI-generated information, the effects of AI use on critical thinking and the growth of dishonest practices. Focus-group participants likewise repeatedly identified hallucinations, plausible but inaccurate outputs, insufficient verification skills, unclear institutional rules, data-protection risks, weaknesses in current assessment and the need to retain final human responsibility. The programme's absence of explicit competence in these areas is therefore confirmed by multiple sources, although the current practices of students and staff within Medical and Preventive Medicine specifically still require local verification.

The programme's public-health profile makes these omissions material. Graduates are expected to analyse morbidity, assess environmental and occupational risks, conduct epidemiological surveillance, interpret research, produce statutory records, and make sanitary-epidemiological judgements. These are data-intensive, safety-relevant activities in which automated methods may support—but must not replace—professional reasoning. The curriculum already includes forecasting, modelling, GIS-based monitoring, statistical processing and extensive practice; the priority is therefore to make competence expectations explicit, add responsible-AI and data-governance concepts, and strengthen discipline-specific application and verification.

Initial directions are: revise programme-level outcomes and mappings; update ICT and quantitative content; embed responsible AI and data governance across the programme; extend epidemiology, risk-assessment and GIS teaching towards interpretable predictive analytics; introduce supervised practice with appropriately governed public-health datasets; and review assessment so students demonstrate verification, documentation and accountable judgement. Bioinformatics or genomic-surveillance applications should remain a future option pending evidence of staff expertise, datasets and infrastructure.

The programme is analysed as a five-year, 300-ECTS Bachelor's degree, in accordance with its 6B10119 code, cover designation and the confirmed programme classification. Isolated references to NQF level 7, "Master", "Magistrature" and a master's student or project are treated as source-document template or typing errors and are not used as analytical evidence.

2. Programme profile and documentary basis

2.1 Programme identity and professional profile

The programme is identified on the cover as "6B10119 Medical and Preventive Medicine" and in the passport as "Medical and preventive work." It belongs to training area 6B101 Healthcare and educational-programme group BM089. Its stated purpose is to train specialists in hygiene and epidemiology who can protect public health, ensure sanitary and epidemiological welfare, and implement sanitary and hygienic supervision. The mission emphasises professional competence, responsiveness to labour-market needs, and graduate competitiveness.

The intended graduate profile is a doctor-hygienist and epidemiologist. The seven programme learning outcomes cover application of fundamental, socio-behavioural, hygienic and epidemiological sciences; communication using modern information and communication technologies; sanitary and epidemiological supervision; application of healthcare regulation and reporting; evidence-based interpretation of research using modern methods of information collection, processing and analysis and principles of bioethics; preventive action; and lifelong learning.

Evidence: passport and mission, PDF p. 3 (document p. 4); programme learning outcomes, PDF p. 4 (document p. 6).

2.2 Level, duration and credits

Medical and Preventive Medicine 6B10119 is analysed as a Bachelor's programme with a duration of five years and a total volume of 300 ECTS. This classification is supported by the programme code and the cover designation "bachelor course" and has been confirmed for the present analysis. The passport and curriculum contain isolated NQF 7 and Master's-level labels. These are known template or typing errors and are disregarded rather than interpreted as evidence about the programme level. References to research work, graduate practice and the final project are therefore described in level-neutral Bachelor's terminology throughout this report.

Evidence: programme title and level designation, PDF p. 1; duration and credit volume, PDF p. 3 (document p. 4); curriculum and final certification, PDF pp. 7–8 (document pp. 9–10). Source-document Master's labels were excluded as confirmed typographical/template artefacts.

2.3 Curriculum structure and practice

The curriculum totals 300 ECTS and is distributed across five courses/years. It includes 56 ECTS of general education, 76 ECTS of basic disciplines, 122 ECTS of professional disciplines, 30 ECTS of internships, 13 ECTS of research work and 9 ECTS of professional/educational practice, alongside final certification. Relevant foundations occur early through ICT in course I and biostatistics and research methodology in course II. Public-health, hygiene and epidemiology content intensifies in courses II–IV; internships and final work are concentrated later.

Practical components include microbiological laboratory practice; professional practice as an assistant physician-hygienist and epidemiologist; internships in hygiene, epidemiology and sanitary-epidemiological examination; experimental research; and a final project. The practical-skills register covers risk-factor identification, environmental sampling, morbidity calculations, epidemiological study design, causal hypotheses, retrospective morbidity assessment, outbreak investigation, surveillance and statutory reporting. These components are well suited to supervised data-analysis activities, but the document does not state that AI is currently used in them.

Evidence: curriculum, PDF pp. 5–8 (document pp. 7–10); practice descriptions, PDF pp. 18–19 (document pp. 20–21); practical skills, PDF pp. 21–23 (document pp. 23–25).

2.4 Documents reviewed, extraction and limitations

The sole source is KZ Medical and Preventive Medicine(1).pdf, a 24-page, image-only scan of Revision 1 of the 2023 educational programme. The substantive curriculum was already in English. Pre-analysis therefore consisted of OCR extraction, removal of the repeated Kazakh/Russian institutional header and page counters, and conservative correction of obvious OCR and spacing artefacts. Terminology was normalised only where the intended English meaning was clear; for example, "communal hygiene" is retained because it is the document's module title, while broken word joins were repaired. Handwritten approval/validity dates and several abbreviations remain unclear and were not used analytically.

The contents list change-registration and faculty sections on document pages 27–28, but the supplied PDF ends at document page 26. The resource section merely points to external databases or lists—material resources, methodological support, laboratories/centres, software, facilities, practice bases, staff, information resources and electives—without supplying their contents. Consequently, current delivery practices, named staff expertise, actual software, datasets, infrastructure, planned amendments, accreditation status and partner arrangements cannot be evaluated. Course descriptors, detailed assessment rubrics and examples of student work were also unavailable.

Translation/terminology queries for KazNMU: confirm whether “CIME” is an institutional programme-type abbreviation; whether “course” columns I–V correspond exactly to study years; the official English Bachelor’s award and professional qualification titles; and the precise official title of the GIS elective, which appears in the curriculum as “Social and hygienic monitoring” but in the attainability matrix as “Conducting socio-hygienic monitoring using geoinformation systems and public health risk assessment.”

3. Existing AI- and digital-related provision

3.1 Overall assessment

The documentary evidence supports a distinction between data/digital foundations and AI integration. Digital information handling, medical information systems, biostatistics, research methods, epidemiological indicators, forecasting and GIS are explicitly or partially present. AI itself is not identified. The programme’s strongest current contribution is therefore readiness for AI-related modernisation rather than existing AI competence.

Coding follows the requested scale: 0 = not identified; 1 = partial or implicit presence; 2 = explicit presence; N/E = not evaluable. A score of 2 records explicit provision in the named analytical area; it does not imply comprehensive depth. General references to “modern technologies,” “modern IT,” modelling or innovation were not coded as explicit AI.

3.2 Selective mapping matrix

Module / component	Course	Status	Found.	Applied AI	Critical	Ethics / gov.	Discipline application	Evidence / justification
Information and Communication Technologies	I	Required	2	0	0	1	1	Search, collection, storage, processing, distribution and analysis of information; applications, cloud/network resources and medical information systems. Safe use is stated, but no AI, programming or data-governance detail. PDF pp. 5, 8 (doc. pp. 7, 10).
Basics of Academic Integrity and Anti-Corruption Culture	I	University component	0	0	1	2	0	Explicit academic honesty, openness and liability for violations; not connected to AI-assisted work, data provenance or automated authorship. PDF pp. 5, 9–10 (doc. pp. 7, 11–12).
Biostatistics	II	University component	2	0	1	0	1	Explicit medical statistics for research and practical health problems. Methods, software, reproducibility, interpretation limits and advanced modelling are not described. PDF pp. 5, 10 (doc. pp. 7, 12).

Fundamentals of Scientific Research Methodology	II	University component	1	0	1	1	1	Research stages, theoretical/experimental research and reporting. PLO5 links research interpretation to evidence and bioethics, but AI-specific validation is absent. PDF pp. 4–5, 10 (doc. pp. 6–7, 12).
Public Health (basic and professional courses)	II–III	University component	2	0	1	1	2	Statistical processing, demographic indicators, questionnaires, reporting and forecasting are explicit. No automated decision support, model validation or algorithmic governance. PDF pp. 6, 13–14 (doc. pp. 8, 15–16).
Introduction to Epidemiology with Fundamentals of Evidence-Based Medicine	II	Professional / UC	2	0	2	1	2	Epidemiological study types, statistical indicators, risk factors and degrees of evidence. Strong verification base, but no algorithmic evidence appraisal. PDF pp. 7, 14 (doc. pp. 9, 16).
Epidemiology of Non-Communicable Diseases	III	Professional / UC	1	0	1	0	2	Epidemiological analysis of causes and risk factors across population groups and prevention; digital methods are unspecified. PDF pp. 7, 14 (doc. pp. 9, 16).

Conducting socio-hygienic monitoring using geoinformation systems and public health risk assessment	IV	Elective option	2	0	1	1	2	Explicit GIS-based monitoring and risk assessment in a professional context. Data quality, privacy, spatial bias and AI/ML are not stated. PDF pp. 7, 15 (doc. pp. 9, 19).
Methods for predicting environmental health quality	IV	Elective option	1	1	1	0	2	Forecast types, modelling and environmental risk assessment are explicit. AI is only a possible extension, not documented provision. PDF pp. 7, 15–16 (doc. pp. 9, 19–20).
Experimental research / final project	IV–V	Required	1	0	1	1	1	Collection and analysis of hygienic research using modern experimental methods; PLO5 supplies evidence and bioethics. No digital workflow, reproducibility or AI-use requirements. PDF pp. 7–8, 19 (doc. pp. 9–10, 21).

Practice and internships	II, IV–V	Required	1	0	1	1	2	Population-health information, morbidity analysis, surveillance, examinations, legal records and laboratory measurements are practised. Actual digital systems and data safeguards are not documented. PDF pp. 7–8, 18–23 (doc. pp. 9–10, 20–25).
Assessment strategy	Across programme	Required framework	N/E	0	1	1	N/E	Tests, presentations, exams and interviews are mapped to outcomes; case studies, journal club and research projects are teaching methods. No AI-use policy, process evidence or assessment of output verification is stated. PDF p. 20 (doc. p. 22).

Abbreviations: Found. = technological foundations; Critical = critical AI literacy; UC = university component. “Discipline application” records explicit or partial data/digital relevance to public health, epidemiology or biomedical practice; it does not convert non-AI analytics into evidence of AI.

3.3 Findings by analytical area

A. Technological foundations

The ICT course explicitly covers information search, collection, storage, processing, distribution and analysis, use of applications and cloud/network resources, and familiarity with medical information systems. Biostatistics supplies medical-statistics foundations; Public Health includes statistical processing, questionnaires, indicators, reporting and forecasting; epidemiology courses cover study design, risk factors and morbidity indicators; and the GIS elective adds spatial monitoring. These are meaningful foundations. However, the programme does not document programming, database design, data cleaning, data standards, reproducible computational workflows, machine learning or data mining. The resource list mentions software but does not identify what is available.

B. Applied use of AI

No explicit applied-AI provision was identified. Forecasting and modelling in Public Health and Methods for Predicting Environmental Health Quality, and GIS-based monitoring in the elective, are adjacent to AI-enabled practice but remain conventional analytic concepts in the evidence supplied. The document does not name generative AI, automated analysis, recommendation systems, simulation-based decision support or professional AI applications. It also provides no evidence that current teaching uses such systems informally.

C. Critical AI literacy

The programme contains useful preconditions for critical literacy: evidence-based medicine, degrees of evidence, research interpretation, quality assurance, case studies, journal clubs and research projects. Yet none is explicitly applied to algorithmic outputs. No learning outcome requires students to verify AI-generated claims, detect fabricated or implausible output, evaluate training-data relevance, interpret model performance, distinguish correlation from deployable prediction, assess uncertainty, or recognise bias and distribution shift. Critical thinking is stated in Philosophy, but a general statement is insufficient evidence of AI literacy.

D. Ethics and governance

Academic integrity, anti-corruption culture, bioethics and regulatory compliance are explicit strengths. The programme also stresses safe information use in ICT and legal documentation in professional practice. Nevertheless, privacy, personal-data protection, consent and lawful secondary use of health data are not explicit in the supplied descriptions. Nor are transparency, explainability, accountability for automated recommendations, human oversight, audit trails or academic rules for AI-assisted work. Existing ethics and law components are therefore relevant curricular anchors, not evidence of complete AI governance.

E. Discipline-specific applications

The most promising discipline-specific locations are epidemiological surveillance, NCD epidemiology, public-health risk assessment, environmental and occupational health forecasting, GIS-based socio-hygienic monitoring, laboratory and outbreak data, and final research. These align closely with the graduate profile. Biomedical modules in biology, microbiology, immunology and laboratory practice could also support later bioinformatics or genomic-surveillance applications, but the current descriptors do not document sequence analysis, omics data, computational biology or AI-assisted laboratory interpretation. Diagnostic imaging is not central to the documented profile and should not be treated as a priority merely because the programme sits within health sciences.

4. Main strengths and gaps

4.1 Strengths and development assets

- A coherent quantitative and evidence base: ICT, biostatistics, research methodology, public-health statistics and epidemiology are positioned across the first three courses and can support progressive competence development.
- A professional profile built around data-intensive decisions: surveillance, morbidity analysis, environmental and occupational risk, statutory reporting, outbreak investigation and health forecasting create authentic contexts for responsible analytics.
- Explicit evidence and bioethics in PLO5: this gives a programme-level basis for requiring transparent, verifiable and ethically justified use of digital and AI-supported analysis.
- A GIS-oriented elective and an environmental forecasting elective: these are the clearest existing curricular bridges to advanced analytics and spatial or predictive methods.
- Extensive practice and internships: laboratory work, sanitary-epidemiological examination, professional practice and final research allow competence to be demonstrated in realistic workflows rather than only described theoretically.
- Teaching and assessment methods that can be adapted: case studies, journal club, research projects, presentations, examinations and interviews can support critique, defence and verification of analytical outputs.

4.2 Principal gaps

- AI is absent at the level of named content and outcomes. No explicit machine-learning, generative-AI, automated-analysis or algorithmic-decision-support competence was identified.
- The digital foundation is broad but underspecified. Programming, databases, data quality, data standards, provenance, reproducibility and secure data handling are not documented.
- Professional application stops at statistics, monitoring, modelling and forecasting. The programme does not show how students would compare conventional and AI-based methods or judge when automation is inappropriate.
- Critical verification is not formalised. Evidence-based medicine provides a strong platform, but reliability, hallucinations, overfitting, calibration, interpretability, external validity, bias and dataset shift are absent.
- Governance is fragmented. Academic integrity and bioethics exist, yet privacy, data protection, transparency, responsibility and human oversight for AI-supported public-health decisions are not explicit.

- Assessment does not require process evidence. The documented formats do not state that students must disclose AI assistance, document data lineage, retain an audit trail, reproduce analyses or defend the limitations of automated output.
- Advanced biomedical data applications are not visible. Bioinformatics, pathogen genomics and computational surveillance are not identified, although biology, microbiology and epidemiology provide possible future anchors.
- Resources and delivery capacity cannot be assessed. The document refers to databases holding staff, software, laboratories and resources, but these were not supplied.

4.3 Competences potentially practised but not formally expressed

Students may already use statistical software, electronic surveillance records, laboratory information systems, GIS or digital reporting tools during coursework and placements. They may also encounter automated functions in routine platforms. None of this can be inferred as current provision because the documentation does not identify systems, tasks, datasets or assessment evidence. A curriculum-mapping exercise should therefore distinguish genuinely existing delivery from new EduCATIA proposals. Where competences are already practised, the least disruptive intervention is to express them as outcomes and assess them consistently.

4.4 Assessment implications

Current assessment combines tests, presentations, exams and interviews, while teaching includes case studies, regulatory-document work, journal club and research projects. This supports knowledge and oral defence but does not demonstrate data-workflow quality. Modernisation should examine whether assessments elicit data selection, cleaning, documentation, reproducibility, interpretation, verification and accountable professional judgement. The aim is not to prohibit AI assistance but to ensure that a graduate can explain the evidence chain, identify unsafe output and remain responsible for the conclusion.

5. Comparison with empirical findings

The comparison draws on the overall EduCATIA questionnaire findings and the cross-institutional focus-group report. The questionnaire evidence is descriptive and self-reported, and most results are not specific to Medical and Preventive Medicine. Similarly, the focus groups include participants from several institutions and disciplinary backgrounds. The findings can therefore confirm the broader relevance of the identified competence needs, but they cannot establish how frequently each issue occurs within this programme without additional KazNMU programme-level evidence.

Identified need	Questionnaire/focus-group evidence	Curriculum evidence	Preliminary conclusion
Foundational AI knowledge and discipline-specific applications in epidemiology, surveillance and public-health analysis	Advanced self-perceived AI knowledge was uncommon among both students and teachers, at approximately 7%, while only around one third of students reported recent university training or AI teaching within their programme. Medical students showed particularly strong demand for further discipline-specific learning despite comparatively limited formal integration. Among teachers classified in medicine and health sciences, 51.4% reported AI training and 74.9% reported transferring field-specific competences, but frequent use was comparatively low at 33.9%, suggesting a need for structured and contextually relevant provision rather than assumptions based on general adoption. Focus-group participants also described student AI learning as frequently self-taught and recommended systematic instruction linked to professional contexts.	ICT, Biostatistics, Research Methodology, Public Health, Epidemiology, GIS-oriented monitoring, forecasting, practice and research provide substantial foundations. However, no module or programme outcome explicitly covers AI, machine learning, generative AI, automated decision support or the comparison of conventional and AI-supported public-health methods.	**Confirmed by multiple sources.** The curriculum gap corresponds to broader evidence of limited advanced knowledge, uneven formal education and demand for discipline-specific learning. The exact applications, depth and sequencing required for Medical and Preventive Medicine remain programme-specific and should be verified with staff, students and professional stakeholders.
Output verification, error detection, bias, hallucinations and human responsibility	In the teacher questionnaire, 84.4% expressed concern about the reliability of AI-generated information and 82.9% were concerned about effects on students' critical thinking. Focus-group participants	Evidence-based medicine, epidemiological study design, biostatistics, research methodology and bioethics provide strong adjacent foundations. Nevertheless,	**Confirmed by multiple sources.** Verification and accountable judgement are among the clearest cross-source priorities. For this programme, they should be

	repeatedly described AI outputs that appeared convincing but contained incorrect facts or hallucinations. They emphasised deficiencies in fact-checking, recognition of bias, validation of generated teaching materials and the ability to distinguish assistance from substitution. Participants also stated that final educational and professional decisions must remain subject to human review because AI systems are not error-free.	the curriculum does not explicitly require students to verify AI-generated outputs, identify hallucinations or bias, assess calibration or external validity, interpret model limitations, communicate uncertainty or retain accountable human oversight.	connected specifically to morbidity analysis, epidemiological surveillance, environmental and occupational risk, forecasting, GIS analysis and sanitary-epidemiological decisions.
Transparent and responsible AI use, data protection, academic integrity and assessment redesign	Teachers reported substantial concern about increased dishonest practices, at 79.5%. The questionnaire also identified assessment as an area of particular tension and concluded that widespread student use should be accompanied by explicit guidance. Focus-group participants reported unclear or inconsistently communicated rules, unsafe use of commercial platforms, insufficient attention to personal-data exposure and difficulty determining whether submitted work represented students' own competence. They recommended disclosure requirements, approved tools, hybrid assessment, oral defence, process	Academic integrity and bioethics are explicitly present, and the programme uses tests, presentations, examinations, interviews, case studies and research projects. However, the documentation does not connect integrity or bioethics to AI use, health-data protection, disclosure, data provenance, transparency, audit trails or responsibility for AI-assisted decisions. Assessment rules do not distinguish unaided work from supervised or AI-enabled work and do not require students to document,	**Confirmed by multiple sources.** Responsible use and assessment redesign should be treated as high priorities rather than optional additions. The specific rules governing personal and health data, approved tools, disclosure and assessment formats require verification with KazNMU and alignment with applicable institutional and professional requirements.

	evidence and final human review rather than reliance on automated detection or grading.	verify and defend automated outputs.	

The comparison supports prioritising foundational and discipline-specific AI literacy, critical verification, responsible data use, transparent disclosure, human oversight and assessment redesign. Inclusion and accessibility remain relevant EduCATIA concerns, but the reviewed curriculum and available programme-specific empirical evidence do not establish them as an immediate defining need for Medical and Preventive Medicine. They should therefore be classified as **not an initial priority** in this preliminary programme analysis, while accessibility requirements should still be considered when learning resources and practical activities are designed.

The comparison does not establish that the identified gaps are absent from actual teaching practice. Staff or students may already use statistical software, GIS, electronic surveillance systems or AI-supported tools without these activities being formally represented in module descriptions or learning outcomes. Current delivery, informal practice and programme-specific perceptions should consequently be verified before final curriculum amendments are formulated.

6. Initial directions for modernisation

The directions below are preliminary and evidence-based. They identify curricular locations and dependencies without fixing credits, hours, named tools, syllabi or implementation schedules. A standalone module is not recommended at this stage because the strongest needs can be distributed coherently across existing ICT, quantitative, research, ethics and professional components. A distinct module should be reconsidered only if later mapping shows that cross-programme integration cannot produce an assessable, coherent competence sequence.

Modernisation directions matrix

Suggested change	Evidence / need	Intervention type	Priority	Curricular location	Expected benefit	Dependency / verification
Make AI- and data-related graduate competences explicit	PLO5 covers information analysis, evidence and bioethics, but no PLO names AI, verification, data governance or accountable automated support.	1. Make existing competences explicit	High	Programme learning outcomes; attainability and assessment matrices	Creates assessable expectations and prevents AI competence from depending on informal delivery.	Confirm national/sectoral outcome constraints and map existing delivery before drafting amendments.
Update digital and quantitative foundations	ICT, biostatistics and research methodology are present; programming, databases, data quality, provenance and reproducible analysis are not documented.	2. Update existing content	High	ICT; Biostatistics; Fundamentals of Scientific Research Methodology	Provides the minimum data foundation needed for safe later use of predictive or AI-supported methods.	Verify entry-level competence, available software, teaching expertise and access to de-identified data.
Embed responsible AI and health-data governance	Academic integrity and bioethics are explicit, but privacy, data protection, bias, transparency, accountability and human oversight are absent.	3. Add a cross-programme unit	High	Academic Integrity; ICT; research methodology; regulatory module; professional practice	Connects ethics and regulation to real data and automated decisions across the programme.	Confirm applicable institutional policies, legal content and ownership across modules; avoid duplication.

Strengthen interpretable predictive analytics in public health and epidemiology	Statistics, evidence-based medicine, forecasting, risk assessment and GIS are established; AI/ML and model validation are absent.	4. Strengthen discipline-specific application	High	Biostatistics; Public Health; Epidemiology; GIS/risk and forecasting electives	Allows graduates to evaluate predictive results, uncertainty and limitations in surveillance and risk decisions.	Verify mathematical prerequisites, dataset availability and whether elective access is sufficient for all graduates.

Modernisation directions matrix (continued)

Suggested change	Evidence / need	Intervention type	Priority	Curricular location	Expected benefit	Dependency / verification
Develop supervised, dataset-based practical activities	Internships and practical skills include morbidity analysis, surveillance, environmental measurements and reporting, but digital workflows are unspecified.	7. Develop practical activities or pilots	Medium	Public-health and epidemiology practice; hygiene internships; sanitary-epidemiological examination; final research	Turns abstract competence into traceable professional judgement using realistic public-health problems.	Requires lawful, documented access to suitable de-identified or synthetic datasets and clear supervision responsibilities.
Review assessment for transparent and accountable AI-assisted work	Current formats do not require disclosure, audit trails, reproducibility, source verification or defence	5. Review assessment	High	Research projects; presentations; interviews; examinations; final project	Assesses reasoning and professional responsibility rather than	Develop common criteria after programme-level outcomes and institutional AI-use rules are clarified.

	of automated output limitations.				unverified output production.	
Explore bioinformatics and genomic-surveillance applications	Biology, microbiology, immunology and epidemiology provide a possible base, but computational biology and omics are not documented.	4. Strengthen discipline-specific application	Future	Medical Biology; Microbiology and Virology; Immunology; infectious-disease epidemiology; laboratory practice	Could connect biomedical data with pathogen surveillance and public-health prevention.	Proceed only after verifying staff expertise, datasets, computing infrastructure, professional relevance and curricular space.
Establish a verified capability and resource map	The resource section refers to staff, laboratories, software and information resources without supplying inventories; planned amendments are missing.	8. Introduce supporting institutional measures	Medium	Programme-wide curriculum governance	Separates current practice from planned change, identifies feasible pilots and prevents unsupported curriculum claims.	Obtain missing pages 27–28, module syllabi, staff profiles, software/laboratory inventory and practice-site information.

6.1 Sequencing principle

A sensible competence progression would begin with information and data foundations, continue through statistics and research integrity, then introduce responsible automated analysis within epidemiology, public health, environmental/occupational risk and GIS, and culminate in practice or final research requiring transparent verification. This is a direction for later design, not a prescription of hours or module order. It uses the programme's existing sequence and avoids isolating AI from the professional decisions in which responsibility matters.

6.2 Rationale for not recommending a standalone module now

The evidence points to distributed gaps spanning foundations, discipline application, verification, ethics and assessment. These competences already have plausible homes in required modules and practice. A new standalone module could create visibility, but it could also remain detached from epidemiological and hygienic decisions or duplicate existing research and ethics content. Later curriculum mapping should test whether integration produces coherent progression and reliable assessment. If it cannot, a new module may then be justified; the present evidence is insufficient for that conclusion.

7. Issues requiring further verification and conclusion

7.1 Priority verification questions

1. Provide the missing change-registration sheet and faculty section (document pages 27–28), and identify any amendments already approved or under development.
2. Confirm the official English Bachelor's award title and professional qualification wording for use in project outputs.
3. Provide current module syllabi and assessment rubrics for ICT, Biostatistics, Research Methodology, Public Health, Epidemiology, GIS/risk assessment, forecasting, practical placements and final research.
4. Identify software, information systems, GIS environments, statistical packages, laboratories, computing resources and datasets actually used in delivery.
5. Document staff expertise in statistics, epidemiological modelling, GIS, data governance, bioinformatics, machine learning and responsible AI.
6. Clarify whether all students take the GIS/risk and forecasting content or whether access depends on elective choice.
7. Verify current rules for personal and health data, de-identification, secondary use, data retention, academic integrity and disclosure of AI assistance.
8. Collect evidence from placements and student work to determine which competences are already practised but absent from formal learning outcomes.
9. Confirm the precise semester/year placement and prerequisites for each proposed integration point.

7.2 Conclusion

Medical and Preventive Medicine is highly relevant to EduCATIA's Biomedical Sciences and Public Health area because its graduates make evidence-based judgements about populations, environments, workplaces, outbreaks and health-system performance. The curriculum already includes a credible chain from information technology and statistics to epidemiology, forecasting, GIS-oriented monitoring, professional practice and research. This creates a realistic basis for modernisation.

Comparison with the EduCATIA questionnaires and focus groups strengthens the initial curriculum findings. The need for explicit foundational and discipline-specific AI education is supported by the limited prevalence of advanced self-perceived knowledge, uneven formal training and strong demand for field-specific learning, particularly among medical students. The absence of formalised verification, error detection, bias and hallucination awareness corresponds closely to teachers' concerns about reliability and critical thinking and to focus-group accounts of plausible but inaccurate outputs. Similarly, the lack of explicit AI-related data protection, transparency, academic-integrity rules, assessment criteria and human oversight reflects recurring empirical concerns about personal-data exposure, dishonest practices, unclear institutional guidance and the validity of student assessment.

These needs may therefore be classified as confirmed by multiple sources rather than as curriculum gaps requiring empirical confirmation. This classification should nevertheless be interpreted cautiously: the questionnaires are descriptive and predominantly consortium-wide, and the focus groups do not constitute a representative account of this specific programme. Local evidence is still needed to determine current use, staff capability, student practices, institutional rules and feasible implementation formats.

The principal need is not to replace the curriculum's public-health identity with generic AI content. It is to ensure that graduates can use and challenge data-intensive and AI-supported methods safely in their own professional context. The most defensible first steps are explicit programme outcomes, strengthened data foundations, responsible AI and health-data governance, interpretable predictive analytics in existing professional modules, practical dataset-based work and assessment focused on verification, transparency and accountability. These directions should remain provisional until the missing amendment pages, detailed syllabi, actual resources, current delivery practices and applicable institutional policies are verified.

References

Kazakh National Medical University. (2023). Educational program: 6B10119 Medical and Preventive Medicine / Medical and Preventive Work, Revision 1. Dosmukhamedov School of Public Health. Source file: KZ Medical and Preventive Medicine(1).pdf. PDF pages 1–24; internal document pages visible through 26.

Curriculum Analysis: 6B10104 – Pharmacy, Kazakh National Medical University (KazNMU)

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Program Passport & General Information

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1. Executive summary

The active KazNMU programme 6B10104 - Pharmacy is documented as a five-year, 303-credit bachelor's programme. Its curriculum contains a credible set of digital and data-related foundations but no explicit AI curriculum. The strongest documented anchors are Information and Communication Technologies, Statistical Methods in Pharmacy, Research Fundamentals, Clinical Epidemiology and Evidence-Based Medicine, Modern Information Technologies in Pharmacy, process automation, mathematical modelling and computer simulation, pharmacovigilance, and research-oriented final work. These components create feasible locations for later AI integration without requiring immediate wholesale redesign.

No reviewed module explicitly covers artificial intelligence, machine learning, data mining, generative AI, AI-supported decision systems, or pharmacy-specific AI applications. Likewise, the documentation does not formalise critical AI literacy: students are not explicitly required to verify AI outputs, identify errors or hallucinations, interpret model limitations, examine bias, communicate uncertainty, or preserve human oversight. Academic integrity is explicitly taught, and professional safety, regulation and benefit-risk evaluation are present, but privacy, personal-data protection, transparency and responsibility for AI-assisted decisions are not documented.

The curriculum therefore appears better positioned for integration than for replacement. High-priority directions are to make AI and data competences explicit in programme learning outcome 7 and related module outcomes; update Modern Information Technologies in Pharmacy; embed verification, reliability and human responsibility in evidence-based medicine, clinical pharmacy and pharmacovigilance; extend academic integrity to transparent AI use and data governance; and adapt assessment so students must document, validate and defend AI-assisted work. Discipline-specific pilots could later address medication safety, drug-information work, pharmacovigilance, pharmaceutical quality, process monitoring and supply operations.

No standalone AI module is recommended at this stage. The reviewed evidence supports staged integration across existing compulsory and elective components; the need for a separate module should be reconsidered only after module syllabi, staff expertise, infrastructure, data access, institutional policies and Pharmacy-specific empirical findings are verified.

The EduCATIA questionnaire and focus-group evidence confirm the relevance of the curriculum gaps identified in this review. AI use is already widespread among students and teachers, but formal degree-level integration and operational guidance remain less developed. The focus groups—including the KazNMU session—identify output verification, fabricated references, bias and local applicability, sensitive-data protection, transparent use, assessment validity, faculty preparedness and continued human responsibility as recurring needs. KazNMU participants also favoured a common foundation combined with repeated discipline-specific integration and reported a marked difference between polished AI-assisted homework and performance in proctored assessment. These findings reinforce the proposed staged integration of AI into existing Pharmacy modules. However, neither source isolates KazNMU Pharmacy students or staff as a separate subgroup, so programme-specific demand and current delivery still require verification.

2. Programme profile and documentary basis

Profile item	Documented information
Institution	Kazakh National Medical University (KazNMU)
Programme	6B10104 - Pharmacy; education field 6B10 Health; programme group B085 Pharmacy
Level / framework	Bachelor's; NQF level 6 and sectoral framework level 6
Duration / volume	Five years; 303 credits; annual distribution 60 / 62 / 62 / 59 / 60
Languages	Kazakh and Russian
Programme status	Marked as active ('Действующая'), Edition 1
Purpose	Preparation of professionally qualified pharmacy specialists for the labour market of Kazakhstan
Source reviewed	KazNMU, Educational Programme 6B10104 - Pharmacy, pp. 3-33

Source: programme passport and curriculum totals (pp. 4, 6-10). The passport visually displays both 'Bachelor' and 'Bachelor of Medicine' in the academic-degree field; this inconsistency requires confirmation.

2.1 Graduate and professional profile

The eight programme learning outcomes cover academic integrity, ethics and deontology (PLO1); organisation of pharmaceutical care (PLO2); marketing (PLO3); pharmaceutical formulation and production (PLO4); quality control (PLO5); professional medicines counselling (PLO6); modern information technology and information search for creative solutions across the medicines and medical-devices lifecycle (PLO7); and research skills in pharmaceutical activity (PLO8) (p. 5). PLO7 is the clearest programme-level entry point for AI-related competence, but its wording establishes only general information-technology and search capability.

The professional profile spans community and hospital pharmacy, clinical pharmacy, pharmaceutical production, quality assurance and control, pharmacognosy, toxicological analysis, pharmacovigilance, management, marketing, logistics and pharmaceutical research. The programme includes compulsory components and four elective trajectories: pharmaceutical technology; organisation, management and economics of pharmacy and clinical pharmacy; pharmaceutical/toxicological chemistry, pharmacognosy and botany; and management and quality assurance of medicines and medical devices (pp. 6-10).

2.2 Structure, practice and final assessment

The curriculum comprises 56 credits of general education, 145 credits of basic disciplines, 98 credits of profile disciplines and 4 credits of final attestation (pp. 6-10). At least nine credits of named training and production practice are listed across the basic and profile cycles. Practice settings include pharmacies, pharmaceutical production, social pharmacy, pharmacognosy, analytical toxicology, management/economics and pharmaceutical analysis and standardisation (pp. 8-10, 27-29).

The curriculum table describes final attestation as independent examination through comprehensive testing and assessment of practical skills using situational tasks (p. 10). The module matrix, however, describes a thesis or project, or preparation for and completion of a comprehensive examination (p. 29). This difference matters for later assessment redesign and should be resolved.

2.3 Documentary basis and limits

- Pages 3-33 were text-extracted and translated into working English; the repeated institutional header and page counter were omitted before analysis.
- The reviewed file contains the programme passport, learning outcomes, curriculum, short module descriptions and outcome mappings, teaching/assessment methods, progression prerequisites, practical skills and resource categories.
- Full module syllabi, detailed learning outcomes, reading lists, assessment briefs and samples of student work were not supplied; absence from the reviewed document is therefore not proof of absence from delivery.
- The programme is marked active, but the approval date is blank. Accreditation is checked as present, while the accreditation period and body are blank (p. 4).
- The curriculum document provides no current-delivery evidence, planned amendments, staff expertise profiles, detailed infrastructure inventory, datasets,

software list or institutional AI/data policy. The focus-group analysis supplies institution-level examples of AI use and preparedness at KazNMU, but it does not establish Pharmacy-specific delivery, resources or approved amendments.

2.4 Relevance of the Pharmacy Degree to EduCATIA and Rationale for Modernisation

The Bachelor's degree in Pharmacy at KazNMU is highly relevant to EduCATIA because it operates at the intersection of healthcare, biomedical science, data use and technology-supported professional decision-making. EduCATIA seeks to modernise selected higher-education programmes in Kazakhstan and Uzbekistan by integrating relevant, responsible and discipline-specific artificial intelligence competences. Pharmacy represents an important target area because the digital transformation of the pharmaceutical sector affects almost every stage of professional practice: pharmaceutical research, medicine development, manufacturing, quality assurance, supply-chain management, pharmacovigilance, clinical decision support and patient counselling.

Pharmacists increasingly encounter large and complex datasets generated through clinical research, medicine-safety monitoring, electronic health systems and pharmaceutical production. AI-supported methods can contribute to identifying potential drug candidates, analysing adverse drug reactions, detecting patterns in medicine use, forecasting demand and supporting the individualisation of treatment. Automated systems are also becoming relevant to manufacturing processes, quality control, stock management and the prevention of medication errors. Consequently, future pharmacists require more than general digital competence. They need to understand what AI-supported systems can and cannot do, how their outputs should be verified and when professional judgement must override or contextualise an automated recommendation.

The programme provides a promising basis for this development. The curriculum already contains digital- and data-related elements, including statistics, pharmacy information systems, process automation, computer simulation, pharmacovigilance, evidence-based medicine and research activities. These components create potential entry points for introducing AI-related learning without separating it from the programme's established professional profile. For example, statistical and research components can support foundational understanding of data quality and algorithmic reasoning, while pharmacovigilance and evidence-based medicine can provide authentic contexts for evaluating automated outputs and distinguishing reliable evidence from unsupported conclusions.

However, the analysis indicates that the documented curriculum does not explicitly address artificial intelligence, machine learning or generative AI. It also does not clearly formalise competences in model-output verification, bias detection, explainability, hallucination awareness, privacy protection or human oversight. This is particularly important in Pharmacy because inaccurate or uncritically accepted AI-generated information may influence medicine safety, contraindication assessment, dosage interpretation, pharmacological research or communication with patients. Responsible AI competence in this field is therefore not merely an additional digital skill; it is connected to patient safety, professional accountability and the pharmacist's ethical duty to make evidence-based decisions.

The programme should also be updated because general technological competence alone does not adequately prepare graduates for the changing professional environment. Students must be able to assess the quality and representativeness of pharmaceutical and health data, recognise possible bias in automated systems, document the use of AI transparently and protect confidential patient or research information. They should also understand that responsibility remains with qualified professionals even when an automated system contributes to analysis or decision support. These competences correspond closely to EduCATIA's emphasis on critical AI literacy, responsible use, data protection, academic integrity and the preservation of meaningful human oversight.

Modernising the Pharmacy degree would therefore serve both an immediate professional need and a broader project objective. It would demonstrate how AI competence can be embedded in a regulated, safety-critical discipline by connecting technological understanding with professional ethics and pharmaceutical practice. The programme can become a strong example of discipline-specific curriculum modernisation: building on existing digital foundations while ensuring that graduates can engage with emerging technologies critically, safely and responsibly. This would strengthen their readiness for contemporary pharmaceutical practice and support EduCATIA's wider goal of developing sustainable AI capacity in Central Asian higher education.

3. Existing AI- and digital-related provision

The analysis of the degree's modules was conducted to create a mapping matrix scoring the AI presence in the degree. A score of 2 indicates explicit coverage in the reviewed text; 1 indicates a partial or implicit foundation; 0 means that the relevant element was not identified; N/E means the documentation does not permit evaluation. General references to innovation, modern technology, automation or information systems are not treated as explicit AI integration.

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3.1 Selective mapping matrix

Module / component	Year	Status	Tech. foundations	Applied AI	Critical AI literacy	Ethics / governance	Discipline-specific app.	Evidence and brief justification
Information and Communication Technologies (English)	1	Current; compulsory; 5 cr.	1	0	0	0	1	Professional use of modern ICT is explicit, but no programming, data science or AI is specified (pp. 6, 10).
Academic Integrity and Anti-Corruption Culture	1	Current; university component; 1 cr.	0	0	0	2	0	Academic integrity, policy, violations and sanctions are explicit. AI use, data governance and privacy are absent (pp. 6, 12).
Statistical Methods in Pharmacy	2	Current; compulsory; 4 cr.	2	0	1	0	2	Correlation, regression and statistical processing of pharmacological results are explicit. Reliability/AI validation is not (pp. 6, 14).
Research Fundamentals	2	Current; compulsory; 4 cr.	1	0	1	0	2	Quantitative methods and statistical processing of pharmaceutical research/production data provide a partial foundation (pp. 6, 14).

Clinical Epidemiology and Evidence-Based Medicine	3	Current; compulsory; 4 cr.	1	0	1	0	2	Population morbidity and evidence-oriented reasoning are explicit; digital or AI-supported evidence appraisal is not (pp. 7, 15).
Modern Information Technologies in Pharmacy	3	Current; compulsory; 4 cr.	1	0	0	0	2	Collection/processing of professional information, software implementation and pharmacy information systems across the medicine lifecycle are explicit (pp. 7, 16-17).
Automation of Process-Control Systems in Pharmaceutical Production	3	Current; elective trajectory; 6 cr.	1	0	0	0	2	Control, regulation and management of production processes are explicit; automation is not evidence of AI (pp. 8, 20).
Clinical Pharmacy / Hospital Management	4-5	Current; compulsory; 4 + 4 cr.	0	0	1	1	2	Safe, rational, effective and transparent medicines use provides a responsibility context, but no digital or AI application is stated (pp. 8, 20-21).
Pharmacovigilance Fundamentals	5	Current; compulsory; 4 cr.	1	0	1	1	2	Continuous observation, analysis, safety-information evaluation and benefit-risk assessment are explicit; AI-

								supported signal detection is absent (pp. 8, 23).
Modelling of Chemical-Pharmaceutical Processes	5	Current; elective trajectory; 4 cr.	2	0	1	0	2	Mathematical models and computer simulations for analysis/optimisation of synthesis, production and quality processes are explicit (pp. 9, 26-27).
Practice, practical skills and final work	1-5	Current; required and trajectory-dependent	1	0	1	1	2	Critical analysis, evidence-based conclusions, automated equipment, research and situational tasks are documented; AI-use expectations are not (pp. 27-33).

3.2 Findings by analytical area

A. Technological foundations

The programme provides explicit quantitative and computational foundations through statistics, research methods and an elective modelling course. Modern Information Technologies in Pharmacy introduces information collection and processing, software implementation and pharmacy information systems. Process automation adds a systems-control perspective. However, programming languages, database design, data management, machine learning and data mining are not identified. The ICT module remains too broadly described to determine its technical depth.

B. Applied use of AI

No explicit applied AI was identified. The curriculum does not mention generative AI, automated inference, recommendation systems, predictive analytics or AI-supported professional decisions. Mathematical simulation and automated production control are explicit but are not coded as AI. No documented module applies AI to drug information, pharmacovigilance, medication safety, pharmaceutical quality, clinical decision support, manufacturing, logistics or research.

C. Critical AI literacy

Several components cultivate adjacent reasoning: statistical interpretation, evidence-based medicine, benefit-risk assessment, critical information analysis and justified conclusions. These are strong curricular anchors, but the documentation does not connect them to AI outputs. There is no explicit requirement to verify AI-generated content against authoritative sources, detect fabricated or erroneous output, interpret model performance, consider uncertainty, identify bias or recognise limitations and hallucinations.

D. Ethics and governance

Academic integrity, ethics, deontology, pharmaceutical law, GxP, biological safety and pharmacovigilance are documented. This is an important professional-responsibility base. Nevertheless, no reviewed text addresses personal or health-data protection, privacy-preserving use, transparency of AI assistance, documentation of automated recommendations, accountability for AI-supported decisions, or meaningful human oversight. The academic-integrity module predates or at least does not document AI-specific disclosure and attribution rules.

E. Discipline-specific application

The programme's professional breadth creates multiple credible application sites, particularly pharmacy information systems, pharmacovigilance, medication counselling, hospital medicines management, quality control, manufacturing, process modelling, logistics and research. These remain potential integration locations rather than documented AI provision. The evidence does not support a claim that students currently practise AI for diagnosis, medical imaging, epidemiological prediction, bioinformatics or other health-related uses.

3.3 Teaching, assessment and resources

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The programme maps learning outcomes to case analysis, work with regulatory documents, business games, journal clubs, discussion platforms, research projects and scientific publication (p. 29). Assessment methods include written tests, presentations, examinations and interviews (pp. 29-30), with comprehensive testing and practical situational tasks in final attestation (p. 10). These methods can support AI-related learning, especially source verification, professional judgement and defended decisions. The documentation does not state whether AI use is permitted, prohibited, disclosed or assessed, or whether students must preserve an audit trail.

Resource categories include electronic databases updated annually, laboratories and centres, software, teaching and clinical/practice sites, teaching staff and information resources (p. 33). No actual inventory is included. Staff expertise, computing capacity, licensed systems, access controls, protected datasets, simulated datasets and current pharmacy information systems are therefore N/E.

4. Main strengths and gaps

4.1 Documented strengths and development assets

- Quantitative foundation: The explicit pharmacy statistics course covers correlation, regression and statistical processing of pharmacological results (p. 14).
- Digital professional context: Modern Information Technologies in Pharmacy addresses professional information processing and pharmacy information systems across the medicine lifecycle (pp. 16-17).
- Modelling and automation: Computer simulation and mathematical modelling are explicit in an elective trajectory, while process-control automation is explicitly connected to pharmaceutical production (pp. 20, 26-27).
- Safety and evidence culture: Evidence-based medicine, pharmacovigilance, clinical pharmacy, GxP, quality control and practical analytical skills provide a strong basis for verification and accountable decisions.
- Research and active learning: Research methods, thesis/project options, journal clubs, research projects, case analysis and scientific publication are documented (pp. 14, 29).
- Integrity and professional responsibility: Academic integrity, ethics and deontology are programme-level outcomes and have a dedicated first-year component (pp. 5-6, 12).
- Practice-rich professional profile: Placements and practical skills span community, production, analytical, management, pharmacognosy and social-pharmacy settings (pp. 27-33).

4.2 Principal gaps

- AI foundations are absent: No artificial intelligence, machine learning, data mining or AI-system concepts are explicitly documented. Programming and databases are also not identifiable.
- Applied AI is absent: No professional AI application is expressed as content, learning outcome, practical skill or assessment requirement.

- Critical verification is not formalised for AI: Adjacent critical-analysis competences exist, but there is no explicit output verification, error detection, reliability appraisal, model interpretation, bias analysis or hallucination awareness.
- Governance coverage is incomplete: Academic integrity and professional regulation are present, but privacy, data protection, transparency, responsibility for AI-assisted decisions and human oversight are not documented.
- Content is fragmented: Relevant digital, statistical, modelling, safety and integrity competences are distributed across modules without a documented progression from data foundations to responsible professional AI use.
- Assessment expectations are unclear: The programme does not state how AI-assisted work should be disclosed, verified or defended, or how assessment validity should be protected.
- Resource and delivery evidence remains insufficient at programme level: the focus groups indicate active AI use at KazNMU and identify faculty workload, practical training and organisational support as constraints, but Pharmacy-specific systems, datasets, staff competence and teaching practice remain unavailable.

4.3 Competences that may exist but are not formally expressed

Students may already use digital systems during pharmacy practice, automated equipment in production, electronic sources in journal clubs, statistical software in research or information systems in pharmacy operations. The KazNMU focus group confirms institution-level AI use for literature searches, research screening, data analysis, code translation and preliminary review of manuscripts or assignments, but it does not establish whether or how these practices occur within the Pharmacy programme. Existing activities should therefore be verified before new content is added; where they already occur, the first intervention may be to formalise learning outcomes and assessment criteria rather than create duplicate teaching.

5. Comparison with questionnaire and focus-group findings

The cross-source comparison strengthens the finding that KazNMU Pharmacy has relevant digital, quantitative and professional foundations, but does not yet express a coherent pathway of AI competence. Questionnaire evidence indicates widespread AI use alongside limited formal curricular recognition and strong demand for further discipline-specific learning, especially among medical students. The focus groups explain this mismatch: across institutions, AI use was described as routine but dispersed, advancing faster than explicit learning outcomes, assessment rules and institutional guidance.

This evidence is directly relevant to Pharmacy. KazNMU participants reported AI-supported curriculum and document drafting, literature searches, scientific-publication screening, data analysis, code translation between statistical environments and preliminary review of manuscripts or assignments. These are institution-level examples rather than evidence of Pharmacy teaching. The Pharmacy curriculum includes statistics, research methods, information systems, evidence-based medicine, pharmacovigilance, modelling and automation, but does not explicitly identify AI, machine learning, generative AI or pharmacy-specific AI applications. The combined evidence therefore indicates that formal competence development has not kept pace with actual use.

A first area of convergence is the need for explicit and progressive learning outcomes. The questionnaire suggests that some teachers transfer AI-related competence without students recognising it as structured teaching. Focus-group participants likewise distinguished spontaneous use from formal integration, while KazNMU contributors favoured an outcome-based approach and repeated integration across the medical curriculum rather than ownership by a single department. In Pharmacy, relevant practices may already occur through statistical analysis, electronic information searches, automated production systems or research, but they are not expressed as AI outcomes or assessment criteria. This need is confirmed by multiple sources; the exact progression remains programme-specific and requires syllabus mapping.

Verification and critical judgement are the strongest cross-source priority. Focus-group participants reported incorrect numerical claims, fabricated references and identifiers, non-existent chemical structures, unsuitable clinical recommendations and technically plausible but methodologically incorrect outputs. They stressed that fluent presentation can conceal error and that reliable evaluation depends on prior disciplinary knowledge. Kazakh medical participants also warned that systems trained predominantly on Western datasets may produce recommendations that do not fit Kazakhstan's population, healthcare infrastructure or available resources. The Pharmacy curriculum offers strong anchors in statistics, evidence-based medicine, benefit-risk evaluation and pharmacovigilance, but no explicit AI-output verification, bias appraisal, uncertainty communication or contextual-validity assessment. This gap is confirmed by multiple sources and is programme-specific in its patient- and medication-safety implications.

The combined evidence supports observable Pharmacy competences rather than generic tool use. Students should be able to formulate an appropriate professional problem, justify the selected method, trace data and sources, verify generated information against authoritative pharmaceutical or clinical evidence, identify and correct errors, assess local applicability, disclose AI assistance and defend the final decision independently. Realistic cases in medication counselling, pharmacovigilance, pharmaceutical quality, benefit-risk evaluation, production and hospital medicines management would connect the common AI-literacy foundation to the programme's professional profile. The locations are programme-specific proposals; the competence need is confirmed by multiple sources.

Governance and academic integrity form another area of cross-source agreement. Focus-group participants described personal, patient, research and institutional information being entered into commercial platforms without adequate awareness of storage or reuse. They called for clear approved-use cases, disclosure of AI assistance, suitable alternatives where external accounts are required, and human accountability for consequential decisions. KazNMU was among the groups in which data protection was a major concern, and medical participants treated professional responsibility as non-negotiable. The curriculum includes academic integrity, ethics, deontology, pharmaceutical law and GxP, but not AI-specific disclosure, sensitive-data rules, approved-tool conditions or human oversight. The need is confirmed by multiple sources; the applicable KazNMU procedures require institutional verification.

Assessment redesign is also confirmed by multiple sources. KazNMU participants reported that students could achieve very high results on AI-assisted homework yet perform poorly in proctored examinations. Across the groups, conventional take-home products were considered increasingly weak evidence of independent reasoning, while blanket prohibition and automated AI detection were viewed as inadequate. Proposed responses included declared and traceable use, staged submissions, oral defence, supervised work, portfolios and comparison of assisted and unaided performance. For Pharmacy, selected assessments should continue to test independent foundational and practical competence, while others should evaluate transparent, verified and professionally accountable AI use. Exact rules must be aligned with each learning outcome and the confirmed final-attestation route.

Faculty capacity is a necessary implementation condition. Questionnaire evidence shows strong interest in further training. Focus-group participants consistently argued that faculty development should precede or accompany student training and should be practical, continuous and discipline-sensitive rather than limited to one-off tool demonstrations. KazNMU participants connected this need to heavy teaching and administrative workloads and warned that investment in software would have limited effect without time, training and organisational support. This confirms the institutional need, while the specific competence and workload of Pharmacy staff responsible for information technology, statistics, research, evidence-based medicine, pharmacovigilance, clinical pharmacy, modelling and automation still require verification.

The combined evidence supports a two-level curricular model: a common foundation in responsible AI literacy combined with repeated discipline-specific application. This corresponds to the approach favoured by KazNMU focus-group participants for medical education. In Pharmacy, the common component could be distributed across ICT, academic integrity, statistics, research and pharmacy information technology; professional applications could then be introduced through pharmacovigilance, medication information, clinical and hospital pharmacy, production, quality control, logistics and research. A standalone module is therefore not an initial priority, although the decision should remain open until syllabi, curricular space, staff capacity, infrastructure and policies are reviewed.

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Cross-source synthesis

Identified need	Questionnaire evidence	Focus-group evidence	Curriculum evidence	Cross-source conclusion
Foundational and profession-specific AI competence	AI use is widespread, but only around one third of students report general or field-specific AI teaching; almost two thirds wish to learn more, with especially strong demand among medical students.	Across groups, AI use was widespread but dispersed. KazNMU participants favoured a common foundation with repeated discipline-specific integration.	Digital systems, statistics, research, modelling and automation are present, but AI/ML, generative AI and pharmacy-specific applications are not explicit.	**Confirmed by multiple sources. High priority; Pharmacy-specific demand and application choices require verification.**
Explicit and observable learning outcomes	Teachers report more competence transfer than students recognise, suggesting that some AI learning remains implicit.	Participants distinguished spontaneous use from formal integration. KazNMU contributors called for stronger outcome-based curriculum design.	PLO7 and related modules refer to information technology and information search, but not to AI selection, verification, disclosure or accountable use.	**Confirmed by multiple sources. Existing practices should be mapped and converted into explicit, observable outcomes.**
Verification, error detection, bias, uncertainty and limitations	The questionnaire analysis identifies evaluation of outputs, hallucinations, bias, uncertainty and retention of human responsibility as core competences.	Verification was the most consistent gap. Examples included fabricated references, non-existent chemical structures and unsuitable clinical recommendations; Kazakh medical participants also warned about Western-trained systems that may not fit local conditions.	Evidence-based medicine, statistics and benefit–risk evaluation provide strong anchors, but AI-specific verification is absent.	**Confirmed by multiple sources and programme-specific in its medication- and patient-safety implications. High priority.**

Privacy, integrity, transparency and human oversight	The questionnaire report identifies unclear rules concerning disclosure, citation, sensitive data, approved tools and responsibility for AI-supported decisions.	KazNMU was among the groups identifying sensitive-data exposure as a major concern. Participants supported approved-use cases, disclosure, clear responsibility and human oversight in consequential decisions.	Academic integrity and professional regulation are present, but AI disclosure, health-data protection and human oversight are not documented.	**Confirmed by multiple sources. Institutional procedures and Pharmacy-specific cases require verification.**
Assessment redesign	Widespread use and unclear rules justify authentic assessment, documentation of AI use, supervised tasks and oral defence.	KazNMU participants reported high AI-assisted homework results alongside weak proctored performance. Groups supported traceable use, oral defence, staged and supervised work, and human review rather than reliance on AI detectors.	Existing assessments include tests, projects, presentations, interviews and situational tasks, but AI-use expectations are unspecified.	**Confirmed by multiple sources. Assessment rules should be aligned with the intended learning outcome and independently demonstrated competence.**
Faculty development and institutional capacity	Around half of teachers report university-organised training, while approximately four out of five wish to learn more.	Faculty development was a strong cross-group priority. KazNMU participants linked it to workload and argued that software investment needs time, practical training and organisational support.	Staff expertise, systems, datasets, computing capacity and support arrangements cannot be evaluated from the curriculum.	**Confirmed by multiple sources at institutional level; Pharmacy-specific capacity and resource needs require verification.**

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Evidence limitation

The questionnaire report is aggregated across the EduCATIA respondent population and broad disciplinary groups; it does not measure KazNMU Pharmacy separately. The focus-group analysis is a completed thematic synthesis and includes KazNMU-specific institutional perspectives, but the groups differed in composition and documentation and were not designed as representative or matched samples. The KazNMU session primarily represents medical, public-health, research, management and technical perspectives rather than a distinct Pharmacy subgroup. Its findings can therefore confirm institution-level and health-education needs, but Pharmacy-specific current practice, demand, staff capacity, infrastructure and implementation choices still require direct verification.

6. Initial directions for modernisation

The following directions are preliminary EduCATIA proposals, not approved KazNMU amendments. They avoid final credit allocations, teaching hours, tool choices and detailed syllabi. Priority reflects safety, responsibility, documented curricular need and feasibility. Integration is preferred because the curriculum already contains several relevant compulsory modules.

Suggested change	Evidence / need	Intervention type	Priority	Possible curricular location	Expected benefit	Dependency / verification
Make AI and data competence explicit in programme and module outcomes	PLO7 covers modern IT and information search but does not identify AI, verification or responsible professional use.	1. Make existing competences explicit	High	PLO7; ICT; Modern Information Technologies in Pharmacy; Research Fundamentals	Creates a visible progression and assessable graduate expectation without immediate structural expansion.	Map existing syllabi and confirm programme-learning-outcome amendment rules.
Update the compulsory pharmacy information-technology content	AI methods are absent; focus groups support common foundations plus disciplinary application.	2. Update existing content	High	Modern Information Technologies in Pharmacy; links to Statistics	Provides common foundational literacy and distinguishes ICT, automation, analytics and AI.	Verify current syllabus, staff expertise, software and access to suitable teaching data.
Embed verification, reliability, bias, limitations and uncertainty	AI-critical literacy is absent; focus groups reported fabricated sources, unsafe recommendations and locally inapplicable outputs.	4. Strengthen discipline-specific application	High	Evidence-Based Medicine; Pharmacovigilance; Clinical Pharmacy; Hospital Management	Reduces unsafe reliance on outputs and connects critical AI literacy to professional responsibility.	Use pharmacy-relevant cases; agree authoritative verification sources and performance criteria.

Extend integrity and governance to responsible AI and health-data use	AI governance is absent; focus groups, including KazNMU, prioritised privacy, disclosure, accountability and oversight.	3. Add a cross-programme unit	High	Academic Integrity; pharmaceutical law; research; practice orientation	Creates consistent minimum expectations across modules and protects students, patients and institutions.	Align with institutional policy and applicable data-protection, research and professional requirements.
Introduce small discipline-specific practical pilots	AI application is undocumented; focus groups favoured realistic cases requiring rejection of unsafe recommendations.	7. Develop practical activities or pilots	Medium	Pharmacovigilance; drug information/counselling; quality control; production; logistics; research	Builds applied judgement through bounded tasks such as comparing, checking and documenting AI-assisted analysis.	Confirm data access, privacy safeguards, staff support and whether simulated/synthetic data are required.
Review assessment for an AI-enabled environment	AI-use rules are absent; KazNMU reported a homework–proctored performance gap.	5. Review assessment	High	Module assessments; placements; final project/exam	Preserves assessment validity and rewards disclosure, source tracing, verification and defended	Clarify final-attestation format and establish institution-wide disclosure/documentation expectations.

					human decisions.	
Develop an advanced data/modelling pathway within existing electives	Mathematical modelling, simulation and process automation are explicit but not connected to AI model development or validation.	2. Update existing content	Future	Modelling of Chemical-Pharmaceutical Processes; Process-Control Automation; Statistics	Offers deeper competence for production, quality and research profiles without imposing advanced content on all students.	Depends on staff expertise, computational infrastructure, datasets and elective-trajectory participation.
Establish supporting institutional conditions	Resources are N/E; KazNMU identified workload, training, approved systems and organisational support as dependencies.	8. Introduce supporting institutional measures	Medium	Programme management and cross-university support	Enables safe, coherent and sustainable curriculum changes rather than isolated module experiments.	Inventory staff, systems, protected data access, support services and quality-assurance responsibilities.

Recommendation on a standalone module: not initially recommended. The required minimum competence can reasonably be integrated through the existing compulsory information-technology, statistics, research, evidence, integrity and professional-safety components. A new module should be reconsidered only if syllabus mapping shows that the content cannot be coherently distributed, a coherent body of competence is agreed, and it materially changes the graduate profile.

7. Issues requiring further verification and conclusion

7.1 Source and translation issues requiring inquiry

- Confirm the official awarded degree. The passport displays both 'Bachelor' and 'Bachelor of Medicine' (p. 4), which is unusual for a pharmacy bachelor's programme.
- Confirm the official approval date, accreditation period and accreditation body; the corresponding fields are blank although accreditation is checked as present (p. 4).
- Confirm that the isolated value '5' in the passport is the official duration in years and that 303 credits are defined in the intended credit system.
- Confirm the operative final-attestation route. The curriculum table describes an independent two-stage examination, while the module matrix also allows a thesis/project or comprehensive examination (pp. 10, 29).
- Confirm exact semesters. The curriculum provides study-year distribution but not semester placement.
- Clarify whether all students take the electives in automation and chemical-pharmaceutical process modelling; the four educational trajectories make access profile-dependent.
- Review full syllabi for the ICT, statistics, research, pharmacy information technology, pharmacovigilance, modelling and automation courses before concluding that detailed AI content is absent.
- Verify current teaching practice, staff expertise, software, datasets, electronic databases, information systems, data-protection arrangements and planned curriculum amendments.
- The Russian source contains typographical and layout artefacts. Examples translated by intended technical meaning include 'атоматизации' as 'automation', 'ининновационные' as 'innovative', and 'статическую обработку' in practical skill 12 as likely 'statistical processing' (pp. 20, 31). These should be checked against the editable source.

7.2 Conclusion

The cross-source analysis supports the conclusion that KazNMU Pharmacy is well positioned for staged AI integration, but that its existing digital and quantitative provision does not yet constitute an explicit AI competence pathway. The curriculum provides strong anchors in statistics, research, information systems, evidence-based medicine, pharmacovigilance, modelling, automation, academic integrity and professional responsibility. Questionnaire findings show widespread use and demand for further field-specific learning. Focus-group

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findings confirm that current adoption is broad but fragmented and identify verification, local applicability, data protection, transparent use, assessment validity, faculty preparedness and human responsibility as recurring priorities, including within the KazNMU institutional context.

The principal issue is therefore not simply access to AI tools. It is the development of educational maturity: students and teachers must be able to select appropriate systems, verify outputs, identify errors and bias, protect sensitive data, disclose AI assistance and retain responsibility for professional decisions. In Pharmacy, these competences have direct implications for medication safety, pharmaceutical information, pharmacovigilance, quality assurance, production, research and patient-related practice.

The evidence supports integration through existing compulsory and elective components rather than the immediate creation of a standalone module. PLO7, Modern Information Technologies in Pharmacy, Statistics, Research Fundamentals, Evidence-Based Medicine, Pharmacovigilance, Clinical Pharmacy, Academic Integrity and final assessment provide plausible curricular locations. Faculty development, institutional guidance, approved-tool procedures, data protection and assessment redesign should accompany curriculum changes.

This conclusion remains preliminary because neither empirical source isolates KazNMU Pharmacy as a separate subgroup, and the focus groups provide informed qualitative perspectives rather than representative measurement. Full module syllabi, Pharmacy-specific current teaching and assessment evidence, staff and infrastructure information, institutional policies and consultation with Pharmacy students, teachers and professional partners should therefore be reviewed before final curriculum decisions are made.

References

Kazakh National Medical University. Educational Programme 6B10104 - Pharmacy, Edition 1 (ОП ФАРМАЦИЯ 2024 рус.pdf), reviewed pages 3-33. Russian-language source; working English translation prepared for this analysis.

Measuring Student Sophistication Against DigComp 3.0: A Gap Analysis Based on the EduCATIA Survey Findings

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1. Purpose

This document uses the empirical findings of the **EduCATIA survey** (N = 3,717 students) to **measure the current level of digital / AI sophistication** of students against the **DigComp 3.0** European Digital Competence Framework, and to **identify the gap** between the observed level and the level appropriate for a Bachelor's (BA) student.

The objective is diagnostic: to identify **what specifically can be improved**, at the level of individual DigComp 3.0 competences, so that curriculum development, teacher training, and institutional guidelines within EduCATIA can respond to concrete, evidence-based needs.

2. Framework of the Analysis

2.1 DigComp 3.0 Proficiency Levels

DigComp 3.0 defines four proficiency levels:

Level	Task complexity	Autonomy	Cognitive demand
Basic	Simple, well-defined tasks	With guidance	Remembering / understanding
Intermediate	Well-defined, routine tasks	Independently, some guidance	Applying / analysing
Advanced	Complex tasks	Autonomously, can guide others	Evaluating / creating
Highly Advanced	Complex tasks with unforeseen issues	Fully autonomous, expert level	Specialist knowledge integration

2.2 Target level for a BA student

For a Bachelor's degree student, the reasonable target range is:

- **Entry (Year 1)** → Basic → Intermediate
- **Graduation (Year 3–4)** → Advanced

The **Highly Advanced** level corresponds to Master's / PhD / expert profiles and is not expected of a BA graduate.

Therefore the **BA target = Advanced level by graduation**.

2.3 Method for measuring sophistication from the EduCATIA data

For each DigComp 3.0 competence, the current student sophistication level is estimated by triangulating three types of evidence from the survey:

1. **Frequency of use** (proxy for exposure and functional practice)
2. **Self-perceived knowledge / competence** (proxy for internalised understanding)
3. **Critical, ethical and reflective dimensions** (proxy for higher-order competence)

Each competence is then assigned an **observed sophistication level** and a **gap** relative to the BA target (Advanced).

Gap scale:

- **No gap (0)** — observed level = target

- **Small gap (–1)** — one proficiency level below target
- **Significant gap (–2)** — two levels below target
- **Large gap (–3)** — three levels below target

3. Core Evidence from EduCATIA (Students, N = 3,717)

The following baseline indicators anchor the analysis:

Indicator	%
Use AI at least occasionally	92.4
Use AI often or always	44.9
Self-perceived advanced AI knowledge	7.0
Self-perceived intermediate	47.9
Self-perceived basic	34.3
Self-perceived none	10.8
Attended university AI training (past 2 years)	36.3
Report degree includes field-specific AI teaching	34.0
Learned AI skills from professors	31.7
Interested in more AI learning in their field	64.8
Consider AI-assisted assessment fair	48.9
Perceive AI reduced their critical thinking	36.1

Central finding: the modal student sophistication is **Basic → Intermediate functional use**, not Advanced competence.

4. Competence-by-Competence Gap Analysis

Area 1 — Information search, evaluation and management

4.1.1 Browsing, searching and filtering information

Element	Evidence
Use of AI for tutoring/study support	78.7%
Use of AI for translation	75.1%
Advanced self-perceived knowledge	7.0%

Observed level: Intermediate (functional). Students routinely use AI to search and filter, but the ability to *articulate information needs*, *refine prompts*, and *select the most appropriate tool* — hallmarks of the Advanced level — is not evidenced.

Target for BA: Advanced
Gap: –1 (Small)
Improvement needed: prompt design, tool selection criteria, source triangulation.

4.1.2. Evaluating information ⚠ CRITICAL

Element	Evidence
Teachers concerned about AI reliability	84.4%
Teachers concerned about students' critical thinking	82.9%
Students perceiving reduced critical thinking in themselves	36.1%
Students recognising AI risks (proxy)	Low (not directly measured)

Observed level: Basic. Students use AI outputs but show low evidence of *systematically verifying* them, detecting bias, or identifying hallucinations. The gap between teachers' concern (82.9%) and students' self-perception (36.1%) suggests students **underestimate** the problem.

Target for BA: Advanced

Gap: –2 (Significant)

Improvement needed: verification protocols, bias detection, hallucination identification, source credibility assessment. This is the **single most urgent competence** in the EduCATIA context.

4.1.3. Managing information

Element	Evidence
Students using AI for data analysis	69.7%
Students who identify data analysis as their strongest AI skill	22.0%

Observed level: Basic → Intermediate. High usage, low confidence — students use AI to process data but do not feel proficient. Structured, autonomous data management (Advanced) is not evidenced.

Target for BA: Advanced (particularly in biomedical / public-health fields)
Gap: –2 (Significant)
Improvement needed: structured data handling, verification of AI-processed outputs, reproducibility.

Area 2 — Communication and collaboration

4.2.1. Interacting through and with digital technologies

Element	Evidence
Occasional AI use	92.4%
Use of ≥ 3 tools	13.8%
Use of paid tools	21.5%

Observed level: Basic → Intermediate. Widespread interaction but with a narrow range of tools; students rely on general-purpose applications.

Target: Advanced
Gap: –1 (Small)
Improvement needed: exposure to a broader ecosystem of AI systems (specialist / domain-specific).

4.2.2. Sharing through digital technologies

Element	Evidence
Consider student AI use in assignments fair	65.5%
Practice of disclosing AI use	Not measured; likely low
Institutional guidelines on disclosure	Only 48.0% report they exist

Observed level: Basic. Students share and submit AI-supported work, but **transparent declaration/citation of AI use** is not established practice.

Target: Advanced
Gap: –2 (Significant)
Improvement needed: citation and disclosure norms for AI-generated content.

4.2.3 Engaging in citizenship through digital technologies

Element	Evidence
Interest in AI tutor for administrative tasks	52.5%
Awareness of rights re AI decisions	Not measured

Observed level: Basic. Students are consumers of digital public services but show little evidence of assertion of rights re AI systems (e.g. contesting AI-supported decisions).

Target: Intermediate → Advanced
Gap: –1 to –2
Improvement needed: digital rights literacy, especially in relation to AI decisions affecting them.

4.2.4 Collaborating through digital technologies

Observed level: Intermediate. Implicit collaboration through shared use of AI, but no strong evidence of co-creation practices.

Gap: –1 (Small)
Improvement needed: structured co-creation with AI in group work.

4.2.5 Digital behaviour

Element	Evidence
Teacher concern about dishonest practices	79.5%
Student acceptance of AI in assignments	65.5%

Observed level: Basic → Intermediate. Students engage with AI but the norms of academic-integrity-compliant behaviour are not internalised.

Gap: –2 (Significant)
Improvement needed: shared understanding of academic integrity in AI-mediated work.

4.2.6 Managing digital identity

Observed level: Basic. Not directly measured but implicit in privacy concerns.
Gap: –1 to –2

Improvement needed: management of digital footprint related to AI interactions (prompts contain personal information).

Area 3 — Content creation

4.3.1 Developing digital content

Element	Evidence
Text writing/summarisation (most-proficient task)	25.9%
Report writing with AI	47.0%
Mind maps / study aids	59.8%

Observed level: Intermediate. Students routinely produce AI-supported content, but the *quality dimension* (verification, refinement, disciplinary appropriateness) is not developed.

Target: Advanced
Gap: –1 (Small)
Improvement needed: iterative refinement, quality control of AI outputs.

4.3.2 Integrating and re-elaborating digital content

Observed level: Basic → Intermediate. Students produce content **with** AI, but evidence of critical **integration** with existing disciplinary knowledge is weak.

Target: Advanced
Gap: –2 (Significant)
Improvement needed: integration of AI output with disciplinary sources; not accepting AI text as final.

4.3.3 Copyright and licences

Observed level: Basic. Not directly measured but implicit concerns about dishonest practices (79.5% teacher concern) suggest low competence in copyright/attribution of AI content.

Gap: –2 (Significant)
Improvement needed: rules for copyright of AI-generated outputs, attribution norms.

4.3.4 Computational thinking and programming

Observed level: Basic for most students (Intermediate for the small CS subgroup).
Gap: –1 to –2 depending on discipline
Improvement needed: transversal computational thinking, especially for biomedical, public-health and psychology students.

Area 4 — Safety, wellbeing and responsible use

4.4.1 Protecting devices

Observed level: Basic. Not directly measured.
Gap: –1
Improvement needed: foundational cybersecurity practices, especially with AI-integrated tools.

4.4.2 Protecting personal data and privacy ⚠ CRITICAL for sensitive disciplines

Observed level: Basic. Not directly measured, but the high student demand for AI in psychological support (54.9%) — an area with high data sensitivity — reveals a competence gap.

Target: Advanced (particularly in medicine, biomedical, psychology)
Gap: –2 (Significant)
Improvement needed: privacy risk assessment when using AI tools, especially with personal/sensitive data.

4.4.3 Supporting wellbeing

Element	Evidence
Interest in AI for psychological support	54.9%
Students perceiving reduced critical thinking	36.1%

Observed level: Basic. Students show interest in wellbeing-related AI use but limited understanding of the risks (over-reliance, replacement of human interaction).

Gap: –2 (Significant)
Improvement needed: critical understanding of the limits of AI in wellbeing contexts.

4.4.4 Environmental impacts of digital technologies ⚠ NOT ADDRESSED

Observed level: Cannot be measured — absent from survey.
Assumed level: Basic or below.
Gap: –2 to –3 (Large)
Improvement needed: awareness of AI environmental footprint (energy, water, hardware); this is a **complete gap** in the current EduCATIA diagnostic and must be added.

Area 5 — Problem identification and solving

4.5.1 Identifying and solving technical problems

Observed level: Basic → Intermediate.
Gap: –1
Improvement needed: troubleshooting of AI tools when outputs are inconsistent.

4.5.2 Identifying needs and digital technological responses

Element	Evidence
Students using AI for accessibility	62.5%

Observed level: Intermediate. Accessibility-related use is already established.
Gap: –1 (Small)
Improvement needed: systematic evaluation of which AI tools respond best to specific needs, especially for inclusion.

4.5.3 Identifying creative solutions using digital technologies

Element	Evidence
Medical students wanting field-specific AI learning	78.4%
Overall student demand for field-specific AI	64.8%

Co-funded by the European Union

Observed level: Basic → Intermediate. Strong demand for professional/disciplinary application, but current provision does not enable Advanced-level creative problem-solving.

Target: Advanced
Gap: –2 (Significant)
Improvement needed: discipline-specific AI application, case-based learning, professional scenarios.

4.5.4 Identifying and addressing digital competence needs ⚠ KEY LEVER

Element	Evidence
Interested in learning more about AI (general)	64.3%
Interested in field-specific AI learning	64.8%
Attended AI training in past 2 years	36.3%

Observed level: Intermediate for interest / awareness; Basic for autonomous learning strategies.

Target: Advanced (autonomous, lifelong-learning approach)
Gap: –1 to –2
Improvement needed: students need to be equipped with strategies for continuous, self-directed AI learning — this is the **key lever** because it enables improvement in all other competences.

5. Consolidated Gap Matrix

#	Competence	Observed	Target (BA)	Gap	Priority
1.1	Browsing, searching, filtering	Intermediate	Advanced	–1	Medium
1.2	Evaluating information	Basic	Advanced	–2	CRITICAL
1.3	Managing information	Basic → Intermediate	Advanced	–2	High
2.1	Interacting	Basic → Intermediate	Advanced	–1	Medium
2.2	Sharing (disclosure)	Basic	Advanced	–2	High
2.3	Citizenship	Basic	Intermediate → Advanced	–1 to –2	Medium
2.4	Collaborating	Intermediate	Advanced	–1	Medium
2.5	Digital behaviour	Basic → Intermediate	Advanced	–2	High

2.6	Digital identity	Basic	Advanced	–1 to –2	Medium
3.1	Developing content	Intermediate	Advanced	–1	Medium
3.2	Integrating content	Basic → Intermediate	Advanced	–2	High
3.3	Copyright and licences	Basic	Advanced	–2	High
3.4	Computational thinking	Basic	Intermediate → Advanced	–1 to –2	Medium/High
4.1	Protecting devices	Basic	Intermediate	–1	Medium
4.2	Protecting data / privacy	Basic	Advanced	–2	CRITICAL
4.3	Wellbeing	Basic	Advanced	–2	High
4.4	Environmental impact	Not addressed	Intermediate	–2 to –3	CRITICAL (gap in survey itself)
5.1	Technical problems	Basic → Intermediate	Intermediate	–1	Low/Medium
5.2	Needs & responses	Intermediate	Advanced	–1	Medium
5.3	Creative/disciplinary solutions	Basic → Intermediate	Advanced	–2	High
5.4	Own competence needs	Intermediate (interest); Basic (strategy)	Advanced	–1 to –2	KEY LEVER

6. Where Knowledge Meets High-Level Skill for a BA Student

The **intersection points** where solid knowledge must combine with high-level skill for a BA student — and where the EduCATIA data shows the largest improvement potential — are:

6.1 Critical evaluation (Competence 1.2)

Knowledge: understanding how AI systems generate outputs (probabilistic, non-authoritative).
Skill: systematic verification, hallucination detection, bias identification.
Attitude: critical, non-passive engagement with AI output.
This is the point where a BA student moves from *user* to *competent professional*.

6.2 Privacy and data protection (Competence 4.2)

Knowledge: legal framework (GDPR), what constitutes sensitive data.
Skill: risk assessment before entering data into AI tools.

Attitude: responsible custodianship of personal / third-party data.
Non-negotiable for medical, biomedical, psychology BA students.

6.3 Integration of AI content (Competence 3.2)

Knowledge: disciplinary norms and evidence standards.
Skill: editing, verifying, integrating AI output into a coherent argument.
Attitude: ownership of the final product.
This distinguishes an Advanced student from a Basic-level user.

6.4 Discipline-specific application (Competence 5.3)

Knowledge: professional standards of the discipline + AI capabilities.
Skill: application of AI to authentic professional problems.
Attitude: professional responsibility.
This is the strongest expressed demand (78.4% among medical students).

6.5 Autonomous lifelong learning (Competence 5.4)

Knowledge: awareness of AI's rapid evolution.
Skill: self-directed learning strategies.
Attitude: curiosity, resilience, adaptability.
This is the key lever because it makes improvement in all other competences self-sustaining.

7. Recommendations for Closing the Gap

1. **Priority intervention on Competences 1.2 and 4.2** (both –2, both critical). Every BA programme in EduCATIA should include explicit modules and assessment on critical evaluation of AI outputs and on privacy/data protection.
2. **Introduce Competence 4.4 (environmental impact)**, which is entirely absent from the current EduCATIA survey. Add corresponding survey items in future iterations.
3. **Redesign assessment** to reward Competences 3.2, 1.2 and 2.2 — the areas where BA students most often submit unverified, non-integrated, non-cited AI content.
4. **Discipline-specific pathways** — build Advanced-level Competence 5.3 modules for medicine, biomedical/public health, and psychology.
5. **Empower Competence 5.4** — teach students self-directed AI learning strategies so that gaps continue to close after the intervention ends.
6. **Re-measure** the gap after the intervention using the same DigComp-mapped framework, to demonstrate progress toward the BA-appropriate Advanced level.

8. Conclusion

The EduCATIA survey documents extensive AI **use** but limited AI **sophistication**. Measured against DigComp 3.0, the average student operates at **Basic to Intermediate** level, while a BA student should reach **Advanced** by graduation.

The **largest gaps** are found in:

- **critical evaluation** of AI information,

- **privacy and data protection**,
- **integration** of AI content into disciplinary work,
- **discipline-specific creative application** of AI,
- **environmental awareness** (not measured at all),
- and **autonomous lifelong learning** strategies.

Closing these gaps — not increasing use, which is already saturated — is the central pedagogical task of the EduCATIA project.

References

DigComp 3.0 (Cosgrove & Cachia, JRC, 2025) mapped against EduCATIA Report Survey (Perone, Giordano, Martínez de Carnero, Sapienza – Università di Roma).

DigComp 3.0 competences for BA students — EduCATIA gap-closing framework

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1. How to read this document

Each competence is specified with:

- **Gap** — distance from observed student level to the BA target (from the gap analysis).
- **Exit level** — the proficiency level a BA graduate should reach.
- **Learning outcomes** in the DigComp 3.0 triad:
- **K** = Knowledge (*the student knows / understands …*)
- **S** = Skills (*the student is able to …*)
- **A** = Attitudes (*the student is disposed to …*)
- **Evidence of achievement** — how the outcome is demonstrated and assessed.

AI tagging follows DigComp 3.0: **[AI-E]** = AI-explicit outcome, **[AI-I]** = AI-implicit outcome.

Verb conventions by level

- Intermediate: *identify, describe, apply, use, distinguish, follow*
- Advanced: *evaluate, justify, integrate, design, adapt, critique, guide others*

AREA 1 — Information search, evaluation and management

1.1 Browsing, searching and filtering information

Gap −1 · Exit level: Advanced

Knowledge

- K1.1.1 The student explains how AI-based search and retrieval systems rank and filter results, and why outputs vary between tools. **[AI-E]**
- K1.1.2 The student describes the difference between a search engine, a database and a generative AI system as information sources. **[AI-E]**

Skills

- S1.1.1 The student formulates a precise information need and translates it into an effective query or prompt. **[AI-E]**
- S1.1.2 The student selects the most appropriate tool for a given information need and justifies the choice. **[AI-E]**
- S1.1.3 The student triangulates AI-generated results against at least two independent authoritative sources. **[AI-E]**

Attitudes

- A1.1.1 The student is disposed to reformulate and iterate rather than accept a first result.

Evidence: annotated search log showing prompt iterations, tool choice with justification, and source triangulation.

1.2 Evaluating information ⚠ CRITICAL

Gap −2 · Exit level: Advanced

Knowledge

- K1.2.1 The student explains that generative AI produces statistically probable text, not verified fact, and defines *hallucination*. **[AI-E]**
- K1.2.2 The student identifies the main sources of bias in AI systems: training data, algorithmic design, prompt framing, and reinforcement from user feedback. **[AI-E]**
- K1.2.3 The student describes the limits of AI-generated citations and the phenomenon of fabricated references. **[AI-E]**
- K1.2.4 The student explains criteria of source credibility: authority, currency, peer review, conflict of interest.

Skills

- S1.2.1 The student applies a systematic verification protocol to every factual claim in an AI output before use. **[AI-E]**
- S1.2.2 The student detects and documents hallucinations, including fabricated references and false attributions. **[AI-E]**
- S1.2.3 The student identifies bias or one-sidedness in an AI response and tests it by counter-prompting. **[AI-E]**
- S1.2.4 The student compares outputs from two different AI systems on the same prompt and accounts for divergence. **[AI-E]**
- S1.2.5 The student judges when AI output is unsuitable for the task and states why. **[AI-E]**

Attitudes

- A1.2.1 The student treats AI output as a hypothesis to be tested, never as an authority.
- A1.2.2 The student accepts responsibility for every claim submitted under their own name.
- A1.2.3 The student maintains scepticism proportionate to the risk of the decision at stake.

Evidence: verification dossier — an AI output with every claim traced, verified or refuted, and a written judgement on fitness for purpose. Recommended as a **compulsory assessed task in all EduCATIA BA programmes.**

1.3 Managing information

Gap −2 · Exit level: Advanced

Knowledge

- K1.3.1 The student explains principles of data quality: completeness, accuracy, representativeness, provenance.
- K1.3.2 The student describes what reproducibility requires in AI-assisted data work. **[AI-E]**
- K1.3.3 The student explains the FAIR principles (Findable, Accessible, Interoperable, Reusable).

Skills

- S1.3.1 The student organises, documents and versions data and AI-assisted analyses so that a third party can reproduce them. **[AI-E]**
- S1.3.2 The student validates AI-processed data against the raw source. **[AI-E]**
- S1.3.3 The student records the prompts, tool versions and parameters used in an analysis. **[AI-E]**
- S1.3.4 The student identifies non-representative or incomplete datasets and states the consequences for the conclusions.

Attitudes

- A1.3.1 The student is disposed to document methods transparently rather than only report results.

Evidence: reproducible analysis package — dataset, documented workflow, prompt/tool log, validation notes.

Discipline weighting: highest for Biomedical Sciences and Public Health.

AREA 2 — Communication and collaboration

2.1 Interacting through and with digital technologies

Gap −1 · Exit level: Advanced

Knowledge

- K2.1.1 The student distinguishes categories of AI system: general-purpose assistants, domain-specific tools, retrieval-augmented systems, agents. **[AI-E]**
- K2.1.2 The student explains how context windows, memory and session limits shape interaction. **[AI-E]**

Skills

- S2.1.1 The student uses at least three different AI systems and compares their suitability for a defined task. **[AI-E]**
- S2.1.2 The student structures multi-turn interactions to refine a complex output. **[AI-E]**

Attitudes

- A2.1.1 The student is open to tools beyond the single default application.

Evidence: comparative tool report on one authentic disciplinary task.

2.2 Sharing through digital technologies

Gap −2 · Exit level: Advanced

Knowledge

- K2.2.1 The student states the institutional rules on declaring AI use in submitted work. **[AI-E]**
- K2.2.2 The student explains the difference between AI as a *tool* (e.g. translation, formatting) and AI as a *co-author of substance*, and why each requires different disclosure. **[AI-E]**

- K2.2.3 The student describes accepted formats for citing and declaring AI use. **[AI-E]**

Skills

- S2.2.1 The student writes an accurate AI-use declaration specifying tool, purpose, extent and stage of use. **[AI-E]**
- S2.2.2 The student cites AI-generated material according to a recognised style guide. **[AI-E]**
- S2.2.3 The student decides which uses require disclosure and justifies borderline cases. **[AI-E]**

Attitudes

- A2.2.1 The student regards disclosure as a professional norm, not a penalty.

Evidence: every substantial submission carries a standardised AI-use declaration; a reflective note justifies the disclosure decisions taken.

2.3 Engaging in citizenship through digital technologies

Gap −1.5 · Exit level: Intermediate → Advanced

Knowledge

- K2.3.1 The student explains their rights when a decision affecting them is supported by an automated or AI system, including the right to information and to human review. **[AI-E]**
- K2.3.2 The student identifies the institutional channels for contesting such a decision.

Skills

- S2.3.1 The student formulates a reasoned request for review of an AI-supported academic decision. **[AI-E]**
- S2.3.2 The student participates in institutional consultation on AI policy.

Attitudes

- A2.3.1 The student sees themselves as an actor in, not only a subject of, institutional AI governance.

Evidence: case exercise — drafting a request for review; participation record in a student consultation on AI rules.

2.4 Collaborating through digital technologies

Gap −1 · Exit level: Advanced

Knowledge

- K2.4.1 The student explains how to attribute individual contribution in AI-supported group work. **[AI-E]**

Skills

- S2.4.1 The student co-ordinates a group task using AI tools while keeping contributions traceable. **[AI-E]**
- S2.4.2 The student agrees and documents rules of AI use within a project team. **[AI-E]**

Attitudes

- A2.4.1 The student is disposed to make team AI use explicit rather than tacit.

Evidence: group project with a team AI-use charter and contribution log.

2.5 Digital behaviour (Netiquette)

Gap −2 · Exit level: Advanced

Knowledge

- K2.5.1 The student defines academic integrity in AI-mediated work and distinguishes legitimate assistance from misconduct. **[AI-E]**
- K2.5.2 The student explains why norms of integrity exist in terms of professional trust, not only rule compliance.
- K2.5.3 The student recognises cultural and generational variation in norms of digital interaction.

Skills

- S2.5.1 The student classifies concrete cases of AI use as acceptable, requiring disclosure, or misconduct, and justifies each classification. **[AI-E]**
- S2.5.2 The student adapts register and tone appropriately across digital contexts.

Attitudes

- A2.5.1 The student is disposed to uphold integrity even where detection is unlikely.
- A2.5.2 The student respects diversity in digital interaction.

Evidence: case-based integrity assessment with written justifications; co-construction of a course-level AI use agreement.

2.6 Managing digital identity

Gap −1.5 · Exit level: Advanced

Knowledge

- K2.6.1 The student explains that prompts, uploads and conversation histories may be retained and used for model training. **[AI-E]**
- K2.6.2 The student describes how an AI-related digital footprint can affect professional reputation. **[AI-E]**

Skills

- S2.6.1 The student configures privacy, history and training-opt-out settings in the AI tools they use. **[AI-E]**
- S2.6.2 The student avoids disclosing identifying information about self or third parties in prompts. **[AI-E]**

Attitudes

- A2.6.1 The student takes deliberate responsibility for their digital footprint.

Evidence: documented privacy configuration audit of the student's own AI tools.

AREA 3 — Content creation

3.1 Developing digital content

Gap −1 · Exit level: Advanced

Knowledge

- K3.1.1 The student explains how prompt structure, context and constraints determine output quality. **[AI-E]**
- K3.1.2 The student identifies characteristic weaknesses of AI-generated text: genericity, false confidence, structural repetition. **[AI-E]**

Skills

- S3.1.1 The student designs and iteratively refines prompts to reach a defined quality standard. **[AI-E]**
- S3.1.2 The student produces content in multiple formats — text, visual, structured data — appropriate to audience and purpose. **[AI-E]**
- S3.1.3 The student edits AI output so that the final text meets disciplinary conventions and carries the student's own voice. **[AI-E]**

Attitudes

- A3.1.1 The student holds authorial responsibility for the final product.

Evidence: portfolio showing initial prompt, raw output, successive revisions and final version, with a rationale for each revision.

3.2 Integrating and re-elaborating digital content

Gap −2 · Exit level: Advanced

Knowledge

- K3.2.1 The student explains why AI output cannot substitute for disciplinary reasoning. **[AI-E]**
- K3.2.2 The student describes the evidence standards of their own field.
- K3.2.3 The student distinguishes summarising, paraphrasing, synthesising and arguing.

Skills

- S3.2.1 The student integrates AI-generated material with peer-reviewed disciplinary sources into a single coherent argument. **[AI-E]**
- S3.2.2 The student identifies where AI output conflicts with disciplinary knowledge and resolves the conflict in favour of the evidence. **[AI-E]**
- S3.2.3 The student re-elaborates AI output into a genuinely new synthesis rather than an assembled compilation. **[AI-E]**
- S3.2.4 The student demonstrates conceptual ownership of the submitted content under questioning. **[AI-E]**

Attitudes

- A3.2.1 The student is unwilling to submit content they cannot explain and defend.

Evidence: integrated assignment plus **oral defence** — the most reliable indicator that the Advanced level has been reached rather than simulated.

3.3 Copyright and licences

Gap −2 · Exit level: Advanced

Knowledge

- K3.3.1 The student explains the principal licence types and their conditions of reuse.
- K3.3.2 The student describes the unsettled legal status of authorship and copyright in AI-generated output. **[AI-E]**
- K3.3.3 The student explains why AI training data raises copyright questions for the derived output. **[AI-E]**
- K3.3.4 The student states the terms of use of the AI tools they employ, including ownership of outputs. **[AI-E]**

Skills

- S3.3.1 The student verifies the licence of any material before reuse, including AI-generated material. **[AI-E]**
- S3.3.2 The student attributes sources correctly, including AI systems. **[AI-E]**
- S3.3.3 The student avoids AI-mediated reproduction of protected content. **[AI-E]**

Attitudes

- A3.3.1 The student respects intellectual property as a professional obligation.

Evidence: licence-and-attribution audit of a submitted piece of work.

3.4 Computational thinking and programming

Gap −1.5 · Exit level: Intermediate → Advanced (discipline-dependent)

Knowledge

- K3.4.1 The student explains decomposition, abstraction, pattern recognition and algorithmic sequencing.
- K3.4.2 The student describes at a conceptual level how machine learning models are trained and evaluated. **[AI-E]**
- K3.4.3 The student explains the limits of automation for their disciplinary problems. **[AI-E]**

Skills

- S3.4.1 The student decomposes a disciplinary problem into steps suitable for computational or AI-supported treatment. **[AI-E]**
- S3.4.2 The student reads, tests and corrects AI-generated code or analytical procedures rather than executing them unexamined. **[AI-E]**
- S3.4.3 The student evaluates whether a computational solution is appropriate to the problem.

Attitudes

- A3.4.1 The student is willing to inspect automated procedures rather than trust them by default.

Evidence: documented decomposition and critique of an AI-generated procedure, including at least one error identified and corrected.

Discipline weighting: highest for Biomedical Sciences, Public Health and Cognitive Sciences.

AREA 4 — Safety, wellbeing and responsible use

4.1 Protecting devices

Gap −1 · Exit level: Intermediate

Knowledge

- K4.1.1 The student describes basic cybersecurity measures: updates, authentication, secure networks.
- K4.1.2 The student recognises AI-enabled threats such as deepfake and AI-generated phishing. **[AI-E]**

Skills

- S4.1.1 The student applies protective measures to devices used for study.
- S4.1.2 The student verifies the legitimacy of AI applications and browser extensions before installing them. **[AI-E]**

Attitudes

- A4.1.1 The student treats security as a routine practice.

Evidence: security self-audit checklist.

4.2 Protecting personal data and privacy ⚠ CRITICAL

Gap −2 · Exit level: Advanced

Knowledge

- K4.2.1 The student explains the GDPR principles of lawfulness, purpose limitation, data minimisation and storage limitation.
- K4.2.2 The student identifies special categories of personal data — health, biometric, psychological — and the heightened protection they require.
- K4.2.3 The student explains why entering patient, client or participant data into a general-purpose AI tool may constitute an unlawful transfer. **[AI-E]**
- K4.2.4 The student describes anonymisation and pseudonymisation and their limits.
- K4.2.5 The student explains how AI providers process and may retain submitted data. **[AI-E]**

Skills

- S4.2.1 The student conducts a privacy risk assessment **before** entering any data into an AI system. **[AI-E]**
- S4.2.2 The student anonymises or pseudonymises data effectively where AI use is justified. **[AI-E]**

- S4.2.3 The student decides, and justifies, when an AI tool must **not** be used at all. **[AI-E]**
- S4.2.4 The student exercises data subject rights: access, rectification, erasure, objection.
- S4.2.5 The student selects tools with adequate data-protection guarantees for the sensitivity of the task. **[AI-E]**

Attitudes

- A4.2.1 The student regards third-party data as held in trust.
- A4.2.2 The student applies the precautionary principle when data sensitivity is uncertain.

Evidence: written privacy impact assessment for a realistic disciplinary scenario, including a justified decision not to use AI in at least one case. **Compulsory for Medicine, Biomedical Sciences, Public Health and Psychology.**

4.3 Supporting wellbeing

Gap −2 · Exit level: Advanced

Knowledge

- K4.3.1 The student explains the risks of cognitive over-reliance on AI, including deskilling and reduced independent reasoning. **[AI-E]**
- K4.3.2 The student states the limits of AI in psychological and emotional support, including inability to assess risk or manage crisis. **[AI-E]**
- K4.3.3 The student describes the risks of parasocial attachment to conversational AI. **[AI-E]**
- K4.3.4 The student identifies the human support services available at their institution.
- K4.3.5 The student recognises AI-facilitated harms such as synthetic harassment content. **[AI-E]**

Skills

- S4.3.1 The student regulates their own AI use to preserve independent reasoning, including deliberate unaided work. **[AI-E]**
- S4.3.2 The student recognises situations requiring human professional help and escalates rather than relying on AI. **[AI-E]**
- S4.3.3 The student evaluates a wellbeing-oriented AI application critically before adopting it. **[AI-E]**
- S4.3.4 The student supports peers in the responsible use of such tools.

Attitudes

- A4.3.1 The student values their own cognitive autonomy.
- A4.3.2 The student does not accept AI as a substitute for human care.

Evidence: reflective self-assessment of personal AI dependency with a stated regulation strategy; critical appraisal of one wellbeing AI application with explicit limits and escalation pathway.

4.4 Environmental impacts of digital technologies ⚠ CRITICAL — CURRENTLY ABSENT

Gap −2.5 · Exit level: Intermediate (Advanced in sustainability-related fields)

Knowledge

- K4.4.1 The student explains the environmental footprint of digital technology across its life cycle: extraction, manufacture, use, disposal.
- K4.4.2 The student describes the specific energy and water demands of training and running large AI models. **[AI-E]**
- K4.4.3 The student compares the relative cost of AI-based and conventional approaches to a task. **[AI-E]**
- K4.4.4 The student explains e-waste and the effect of hardware replacement cycles.
- K4.4.5 The student describes how digital and AI technologies can also serve sustainability goals. **[AI-E]**

Skills

- S4.4.1 The student estimates the order of magnitude of environmental cost of a chosen AI workflow. **[AI-E]**
- S4.4.2 The student selects proportionate means, avoiding heavy generative models for trivial tasks. **[AI-E]**
- S4.4.3 The student applies practices that reduce footprint: fewer redundant queries, precise prompting, appropriate model size. **[AI-E]**
- S4.4.4 The student extends device lifespan through maintenance and repair.

Attitudes

- A4.4.1 The student considers environmental cost as one criterion in tool selection.
- A4.4.2 The student rejects the assumption that digital means immaterial.

Evidence: proportionality analysis of an AI-supported workflow with a justified choice of means.

Note: this competence is entirely absent from the current EduCATIA survey instrument. It must be (a) added to the curriculum and (b) added as survey items in the next measurement cycle.

AREA 5 — Problem identification and solving

5.1 Identifying and solving technical problems

Gap −1 · Exit level: Intermediate

Knowledge

- K5.1.1 The student describes common failure modes of AI tools: refusals, truncation, context loss, inconsistency. **[AI-E]**

Skills

- S5.1.1 The student diagnoses whether a poor result stems from the tool, the prompt or the task. **[AI-E]**
- S5.1.2 The student resolves routine technical problems independently and knows when to seek support.

Attitudes

- A5.1.1 The student persists systematically rather than abandoning the task.

Evidence: troubleshooting log with diagnosis and resolution.

5.2 Identifying needs and digital technological responses

Gap −1 · Exit level: Advanced

Knowledge

- K5.2.1 The student explains accessibility requirements and universal design principles.
- K5.2.2 The student describes how AI features — captioning, text-to-speech, simplification, translation — can remove barriers. **[AI-E]**
- K5.2.3 The student recognises where AI tools create new barriers, e.g. through cost or language coverage. **[AI-E]**

Skills

- S5.2.1 The student analyses a need and selects, configures and justifies an appropriate technological response. **[AI-E]**
- S5.2.2 The student adapts their own digital environment for accessibility.
- S5.2.3 The student evaluates the effectiveness of an accessibility solution with the users concerned.

Attitudes

- A5.2.1 The student regards inclusion as a design requirement, not an add-on.

Evidence: needs analysis and evaluated accessibility solution, ideally co-designed with the users concerned.

5.3 Identifying creative solutions using digital technologies

Gap −2 · Exit level: Advanced

Knowledge

- K5.3.1 The student explains current and emerging applications of AI in their own professional field. **[AI-E]**
- K5.3.2 The student describes the professional standards, regulations and liability rules governing AI use in that field. **[AI-E]**
- K5.3.3 The student identifies tasks in their field that must remain under human judgement. **[AI-E]**
- K5.3.4 The student explains the human-centric principle: AI supports, does not replace, professional decision-making. **[AI-E]**

Skills

- S5.3.1 The student designs an AI-supported solution to an authentic professional problem and justifies the design. **[AI-E]**
- S5.3.2 The student defines the boundary of appropriate AI use in a professional scenario. **[AI-E]**
- S5.3.3 The student anticipates unintended consequences and equity effects of the proposed solution. **[AI-E]**
- S5.3.4 The student communicates the role and limits of AI to non-expert stakeholders. **[AI-E]**

Attitudes

- A5.3.1 The student accepts professional responsibility for outcomes reached with AI support.
- A5.3.2 The student keeps human welfare, not efficiency, as the primary criterion.

Evidence: discipline-specific capstone case — a designed AI-supported solution with justification, stated limits, and stakeholder communication.

Discipline weighting: highest expressed demand of any competence (78.4% of medical students).

5.4 Identifying and addressing digital competence needs ✱ KEY LEVER

Gap −1.5 · Exit level: Advanced

Knowledge

- K5.4.1 The student explains how to self-assess competence against a recognised framework such as DigComp.
- K5.4.2 The student describes the rate of change of AI technology and its implications for professional obsolescence. **[AI-E]**
- K5.4.3 The student identifies reliable sources for keeping informed. **[AI-E]**
- K5.4.4 The student recognises the limits of self-assessment, including overconfidence and unconscious incompetence.

Skills

- S5.4.1 The student self-assesses against the 21 DigComp competences and identifies personal priorities.
- S5.4.2 The student designs and executes a personal learning plan with objectives, resources and review points. **[AI-E]**
- S5.4.3 The student learns a previously unknown AI tool independently and documents the process. **[AI-E]**
- S5.4.4 The student supports peers in developing competence, including in disciplinary contexts. **[AI-E]**
- S5.4.5 The student re-assesses and revises the plan periodically.

Attitudes

- A5.4.1 The student accepts competence development as continuous and self-directed.

- A5.4.2 The student is willing to acknowledge gaps in their own competence.
- A5.4.3 The student is disposed to share competence rather than retain it.

Evidence: DigComp self-assessment at entry and exit, a personal learning plan with documented execution, and evidence of peer support. **This is the delivery mechanism that sustains every other outcome after the intervention ends.**

2. Priority Implementation Table

Priority	**Competences**	**Compulsory assessed task**
Tier 1 — All BA programmes	1.2, 4.2, 3.2, 5.4	Verification dossier · Privacy impact assessment · Integrated assignment with oral defence · DigComp self-assessment + learning plan
Tier 2 — All BA programmes	2.2, 2.5, 3.3, 4.3, 4.4	AI-use declaration · Integrity case set · Licence audit · Dependency reflection · Proportionality analysis
Tier 3 — Discipline-specific	1.3, 3.4, 5.2, 5.3	Reproducible analysis package · Procedure critique · Accessibility solution · Capstone case
Tier 4 — Foundation	1.1, 2.1, 2.3, 2.4, 2.6, 3.1, 4.1, 5.1	Integrated into Tier 1–3 tasks

3. Verification of Attainment

Distinguishing genuine Advanced attainment from AI-simulated attainment requires assessment formats that AI cannot produce for the student:

1. **Oral defence** — the student explains and defends submitted content under questioning (verifies 3.2, 5.3).
2. **Process evidence** — prompt logs, revision histories, decision rationales (verifies 1.1, 1.2, 3.1).
3. **Justified refusal** — the student demonstrates deciding *not* to use AI, with reasons (verifies 4.2, 5.3, 4.4).
4. **Error detection tasks** — the student is given flawed AI output and must find the flaws (verifies 1.2, 3.4).
5. **Peer teaching** — the student develops competence in another (verifies 5.4).

4. Note on sources

Competence numbering and the knowledge / skills / attitudes structure follow **DigComp 3.0** (Cosgrove & Cachia, JRC, 2025). Gap values and priority tiers derive from the EduCATIA gap analysis produced in this project. The learning outcomes themselves are **newly formulated for the BA level**: they are aligned to DigComp 3.0 level descriptors but are not verbatim extracts, and should be checked against the framework's own learning-outcome annex before formal adoption.

Conclusion

Gaps shared across all programmes

The strongest shared finding is the gap between actual AI use and formal curriculum integration. Students and teachers already use AI extensively, but programme documentation rarely converts this use into explicit, progressive and assessable competence. Even IT Entrepreneurship, which already teaches machine learning and data mining, lacks a programme-wide progression covering the full range of responsible AI capabilities.

Critical evaluation is the most urgent shared competence gap. Across the programmes, students are not explicitly required to detect hallucinations, verify references, assess bias, evaluate data quality, interpret uncertainty or justify rejection of an AI output. Existing subjects such as critical reading, evidence-based medicine, statistics, research methodology or IT risk management provide valuable foundations, but these foundations have not been systematically extended to AI-supported work.

Privacy, transparency and governance are also shared weaknesses. The curricula contain adjacent content in academic integrity, bioethics, professional ethics, information security or intellectual property, yet they do not establish operational rules for personal and sensitive data, approved tools, disclosure of AI assistance, documentation of automated recommendations or responsibility for final decisions.

Assessment practices have not been adapted adequately to widespread AI use. Programme documents do not consistently specify whether AI is permitted, restricted or prohibited, which uses require disclosure, what process evidence students must provide or how independent competence will be verified. This undermines both academic integrity and the validity of assessment.

Faculty capacity and institutional support remain cross-cutting implementation constraints. Curriculum reform will not succeed if teachers are expected to translate general AI ambitions into subject-specific learning without practical training, time, guidance, secure tools and peer support.

A final shared gap is the absence of reliable evidence about current delivery. Programme documents do not always show which tools are already used, what students practise informally, how staff competence is distributed or which policies have already been adopted. Modernisation should begin with detailed curriculum and capability mapping so that existing good practice is formalised rather than duplicated.

Gaps specific to Education and Health

In Education and language-related programmes, the principal concern is how AI affects the learning process itself. Philology and Language Teaching must integrate AI into instructional design, learning-material development, translation, assessment and accessibility without allowing it to replace the language production, interpretation and independent reasoning that students are expected to acquire.

Education programmes therefore require particularly clear distinctions between learning with AI and substituting AI for learning. Assessment should combine unaided demonstration of core language or pedagogical competence with supervised and transparent AI-supported activities. Teachers must be able to judge whether generated materials are accurate, inclusive, age-appropriate and aligned with learning outcomes.

Psychology occupies an intersection between education and health. Its distinctive gaps concern validity of automated assessment, confidentiality, informed consent, cultural and linguistic bias, professional boundaries, crisis escalation and the risk that persuasive conversational systems will be mistaken for qualified psychological care. AI-supported orientation cannot replace therapy, diagnosis or professional responsibility.

In Pharmacy, the consequences of error relate directly to medicines, patient safety and professional accountability. AI competence must be connected to drug information, adverse-event detection, pharmacovigilance, benefit–risk analysis, pharmaceutical production, medication counselling and quality assurance. Students must learn to reject unsafe recommendations and verify outputs against authoritative pharmaceutical and clinical evidence.

In Medical and Preventive Medicine, the focus is population-level data and decision-making. Relevant gaps include data provenance, representativeness, reproducibility, model calibration, external validity, dataset shift and the local applicability of predictive systems. A model may be technically accurate but unsuitable for Kazakhstan's population, infrastructure or public-health resources. Graduates must therefore assess not only performance but also contextual fitness and possible consequences for communities.

Differences between Uzbekistan and Kazakhstan

The evidence indicates contextual tendencies rather than national rankings. The survey and focus-group samples were not matched, and institutional and disciplinary composition strongly affects the observed differences.

In Kazakhstan, the analysed health programmes provide relatively substantial statistical, epidemiological, information-system and modelling foundations. The principal task is to extend these foundations towards explicit AI competence, locally valid application, health-data governance, transparent assessment and accountable human oversight. Kazakh participants also emphasised the risks of applying models trained on foreign populations, faculty workload, access to suitable infrastructure and the gap between national technological ambitions and usable institutional support.

The IT Entrepreneurship programme illustrates a different Kazakh profile: technical AI-related content is already present, but responsible generative-AI practice, governance, inclusion and assessment remain underdeveloped. Modernisation should build on existing technical maturity rather than introducing another general overview course.

In Uzbekistan, the analysed programmes show greater need for a common and visible AI foundation across heterogeneous tracks. Participants placed particular emphasis on teacher readiness, student dependence on generated content, language learning, unclear institutional rules and assessment redesign. Philology also demonstrates uneven provision among the English, Korean and Eastern Classical Languages tracks.

Psychology in Uzbekistan is additionally shaped by a rapidly developing professional and legal environment. Degree modernisation must address not only AI literacy but also professional governance, deontology, digital psychological assistance, supervised practice, continuing professional development and the absence of sufficient psychological services in higher education.

The shared regional conclusion is that national strategies and infrastructure do not automatically produce curriculum-level competence. Both countries require mechanisms that connect strategic commitments to modules, assessment, staff development, approved tools and professional practice.

Priorities for degree modernisation

Modernisation should begin by making AI-related graduate competences explicit. Each programme should define what every student must know, be able to do and remain responsible for by graduation. These outcomes should be mapped across years and modules so that competence develops progressively rather than through isolated workshops.

A common responsible-AI foundation should be available in every programme. It should include AI concepts and limitations, problem formulation, prompting, verification, source evaluation, data quality, bias, privacy, transparency, academic integrity, inclusion, human oversight and justified non-use.

This foundation should then be applied to authentic professional tasks. Language students should evaluate generated translations and teaching materials. Psychology students should examine the validity and limits of automated interpretation. Pharmacy students should verify AI-supported medication and pharmacovigilance information. Public-health students should evaluate predictive and surveillance models. IT Entrepreneurship students should design and govern AI-enabled products and business processes.

Assessment reform should be implemented in parallel. Each assessment should state the permitted level of AI assistance. Students should provide AI-use declarations and, where relevant, prompts, outputs, revisions, verification records and decision rationales. Oral defence, supervised tasks and error-detection exercises should confirm that the competence belongs to the student rather than being simulated by the tool.

Institutional governance should establish concise and usable rules concerning approved systems, sensitive data, disclosure, intellectual property, procurement, accessibility, monitoring and complaints. The higher the potential impact on students, patients, clients or communities, the stronger the required human review and documentation.

Contribution to curriculum design, capacity building and educational materials

For curriculum design, the findings provide a common architecture and programme-specific priorities. Programme teams should first map existing outcomes, syllabi and assessments against the identified competence areas. They can then decide whether gaps are best addressed by updating existing modules, adding a bounded common unit, distributing content across the programme or introducing a dedicated module. A separate AI module should not be assumed to be the best solution in every programme.

Co-funded by the European Union

For capacity building, the evidence supports differentiated staff pathways. All teachers require foundational critical AI literacy. Teaching staff additionally need competence in task design, assessment and accessibility. Discipline specialists require applied cases and safeguards relevant to their professional fields. Programme leaders require governance, curriculum-mapping and quality-assurance competence. Train-the-trainer activities should enable partner institutions to sustain and extend these capacities after the initial project events.

For educational materials, the project should prioritise reusable resources tied to observable outcomes. These should include verification protocols, hallucination and bias exercises, privacy-impact assessments, AI-use declarations, assessment templates, process logs, discipline-specific cases and examples of justified rejection of AI recommendations. Materials should distinguish durable principles from rapidly changing product instructions and should be made available in the project languages and accessible formats.

The subsequent project activities should pilot these materials in bounded educational settings and evaluate whether they improve competence, assessment validity, responsible practice and institutional clarity. Monitoring should use entry and exit evidence aligned with DigComp, supplemented by programme-specific performance tasks.

The consolidated conclusion is that EduCATIA should not aim principally to increase the frequency of AI use. Use is already widespread. Its contribution should be to make AI-supported education more critical, explicit, assessable, inclusive, locally appropriate and professionally responsible.