Institutional Readiness for Generative AI-Enhanced Assessment and Feedback in Higher Education: Evidence from an Exploratory Study

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***Abstract*—The emergence of Generative Artificial Intelligence (GenAI) technology is changing the ways of assessment and feedback procedures in higher education institutions by allowing for a more flexible and personalized process of learning. However, the effective use of GenAI requires pedagogic design, governance, and implementation strategies. The current study will discuss the institutional prerequisites to implement GenAI in assessment and feedback procedures (Activity A2.2 of the Erasmus+ HEGenAI project). Empirical data were gathered using structured questionnaires completed by educators (n=61) and students (n=254). The descriptive approach involving frequencies, percentages, means, and standard deviations helped to investigate current usage of AI-supported assessment procedures, institutional requirements for GenAI adoption, ways of implementing GenAI, educational advantages of GenAI, and associated risks. The results showed that while GenAI is used extensively to facilitate assessment-related processes, the usage remains predominantly informal and non-institutionalised. It is argued that there is a need to use licensed GenAI solutions, to train educators, to redesign assessment processes, and also to develop an appropriate governance framework. Academic integrity, critical thinking, and AI dependency emerged as the most important risks requiring human attention.**

***Keywords*—Generative AI; assessment; feedback; higher education; academic integrity; formative assessment; institutional readiness**

I. Introduction

The rapid evolution of Generative Artificial Intelligence (GenAI) has become one of the most important trends in modern higher education. Large Language Models (LLMs) such as ChatGPT, Microsoft Copilot, Gemini, Claude, and many others, which initially were limited to content creation, have already evolved and casn be used for numerous activities, especially for assessment and feedback purposes. The capability of providing instant and personalized answers opened up new possibilities to enhance the quality of formative assessment, to facilitate feedback provision, to encourage self-regulated learning, and to relieve educators from extra administrative burden [1] – [5].

The use of GenAI in assessment and feedback goes far beyond automation. Recent research shows that the role of AI should be to assist, but not replace, human academic judgment through authentic assessment, feedback, evaluative judgment, and feedback literacy [6]-[9]. As opposed to paying attention only to efficiency in grading, the current state of the art is aimed at the design of assessment practices that foster critical thinking and high cognitive functions, transparency, and proper use of AI [10]-[13]. In this context, teachers are not the sources of knowledge anymore; they become creators of learning tasks, while students begin interacting with AI, which serves as the agent for learning, reflecting, revising, and creating knowledge independently [10]-[13].

There are also some challenges in implementing GenAI for assessment purposes in universities, however. For example, among the challenges universities encounter when using GenAI for assessment are the issues of governance, ethical use of technology, integrity of the process of assessment, privacy of the data, readiness of educators, and absence of implementation frameworks. While students and educators actively employ the existing open-source AI technologies, higher education institutions often do not have proper policies and pedagogical recommendations related to technological advances [9], [12], [14].

Recognizing these difficulties, the Erasmus+ KA220-HED project HEGenAI – Generative AI for Assessment and Feedback in Higher Education Cooperation aims at developing evidence-based pedagogical models, institutional guidelines, and assessment frameworks for responsible GenAI integration into higher education. Within this project, activity A2.2 is focused on the identification of existing institutional practices, needs for implementation, educational possibilities, and risks of AI-assisted assessment and feedback.

This study provides empirical results from the Mediterranean University of Albania (MUA) as evidence to assist in the creation of institutionally governed GenAI-supported assessment and feedback practices. Instead of analyzing only the process of technology adoption, this study identifies institutional prerequisites for sustainable AI adoption, including technological readiness, assessment redesign, support for educators, mechanisms of governance, and ethical adoption. This study answers the following five research questions to assist further development of pedagogical scenarios and institutional recommendations in the HEGenAI project:

RQ1. What GenAI tools can be integrated into assessment and feedback?

RQ2. What institutional and pedagogical prerequisites ensure GenAI adoption?

RQ3. How should GenAI be integrated into assessment and feedback?

RQ4. What educational advantages can GenAI bring to assessment and feedback?

RQ5. What implementation challenges and risks should be considered by higher education institutions?

Answering these questions provides empirical information regarding the design of a human-centric, pedagogically valid, and ethical GenAI-enabled assessment and feedback ecosystem in higher education, offering guidelines for institutions that want to incorporate AI into their teaching, learning, and assessment processes.

II. Literature Review and Related Work

Recent institution-level research shows a recurring gap between rapid individual adoption of GenAI and the slower development of formal university governance. At the University of Liverpool, a survey of 2,555 students found that 50.9% had used or considered generative AI for academic purposes, while 41.1% explicitly preferred a university-wide policy clarifying acceptable use [14]. A large technical-university survey similarly reported strong student demand for integration and for institutionally supported tools grounded in reliable university-level materials [15]. These findings suggest that adoption is increasingly driven from the learner level upward, while institutional rules, access arrangements, and assessment designs often follow later.

Dual-perspective evidence is particularly relevant to the present study. Kim et al. surveyed 982 students and 76 faculty members and found that approximately 80% supported the development of formal university policies for GenAI use; at the same time, roughly 70% of both groups reported using GenAI less than once per week [16]. This combination of policy demand and still-variable use indicates that institutional readiness cannot be inferred from tool availability alone. It requires governance, staff and student literacy, and pedagogically explicit boundaries for acceptable use.

Institutional policy analyses reinforce this interpretation. An et al. examined guidelines from leading U.S. universities and reported that 94% of the institutions studied had faculty-facing guidance emphasizing the establishment and communication of course-specific GenAI policies [17]. Earlier work also stresses human verification, assessment redesign, feedback literacy, and academic-integrity safeguards [9]-[13]. However, much of the literature either concentrates on student perceptions, policy documents, or broad pedagogical implications in isolation. Fewer studies combine educator and student evidence from the same institution and organize the analysis directly around tools, prerequisites, integration models, educational benefits, and risks. The present study addresses this gap through parallel surveys at MUA and uses the resulting institutional baseline to support implementation decisions within the HEGenAI project.

III. Methodology

A. Study Design

This research has used an exploratory and descriptive quantitative approach to investigate the institutional context of implementing Generative Artificial Intelligence (GenAI) in higher education assessments and feedback. The research has been carried out within Activity A2.2 of the Erasmus+ KA220-HED HEGenAI project and covered the current trends of implementation, the institutional and pedagogical needs, desired ways of implementation, potential educational advantages, and risks. Two similar surveys have been distributed via Google Forms among educators and students. The approach chosen is aimed at creating an empirical foundation for the development of future GenAI-assisted scenarios of assessment and feedback.

B. Sample

The participants of the study consisted of individuals from all four faculties of the Mediterranean University of Albania. In terms of the educator group, there were 61 respondents, including: Law and Human Sciences (n=20; 32.8%), Economic Sciences (n=16; 26.2%), Informatics (n=15; 24.6%), and Medical Sciences (n=10; 16.4%). As for the student group, there were 254 respondents, which included: Informatics (n=101; 39.8%), Law and Human Sciences (n=64; 25.2%), Economic Sciences (n=54; 21.3%), and Medical Sciences (n=35; 13.8%). Thus, thanks to multi-disciplinary participation, it was possible to identify GenAI assessment and feedback practices within the fields characterized by different traditions of pedagogy and varying degrees of technological intensity of tasks. The full demographic breakdown is presented in Table I.

TABLE I. Demographic Profile of Survey Participants (Educators n = 61; Students n = 254)

Characteristic	Category	Educators (n = 61)	Students (n = 254)
Age	18–20 / <28	1 (1.6%)	89 (35.0%)
	21–23	—	63 (24.8%)
	24–26	—	29 (11.4%)
	27+	—	73 (28.7%)
	29–35	11 (18.0%)	—
	36–45	28 (45.9%)	—
	46–55	6 (9.8%)	—
	56–65	11 (18.0%)	—
	66+	4 (6.6%)	—
Experience (educators)	<5 years	5 (8.2%)	—
	5–10 years	18 (29.5%)	—
	11–20 years	28 (45.9%)	—
	21+ years	10 (16.4%)	—
Study cycle (students)	Bachelor	—	182 (71.7%)
	Master	—	50 (19.7%)
	Professional diploma	—	15 (5.9%)
	Doctorate	—	7 (2.8%)
Faculty	Law & Human Sciences	20 (32.8%)	64 (25.2%)

Characteristic	Category	Educators (n = 61)	Students (n = 254)
	Informatics	15 (24.6%)	101 (39.8%)
	Economic Sciences	16 (26.2%)	54 (21.3%)
	Medical Sciences	10 (16.4%)	35 (13.8%)

Convenience sampling technique was applied for all participants following the exploratory nature of the study and the A2.2 research design [7]. The educators and students served as the main actors in the process of evaluation and feedback, which allowed for collecting data on the experiences related to the application and management of GenAI tools.

C. Instruments and Analysis

These surveys were made up of four parts: 1) demographic data; 2) multiple choice questions indicating the types of GenAI technologies employed or allowed and the assessment and feedback activities where they were used; 3) 5-point Likert scale questions relating to institutional needs and training needs (question 9), impact (question 13), benefits in education (question 14), and implementation risks (question 15); and 4) open-ended questions related to the risks of GenAI implementation and the undesirable practices in relation to GenAI. These two surveys were consistent with the five research questions and were developed to explore the role of GenAI in assessment design, feedback provision, learning support, and human judgment.

The analysis remained descriptive throughout. Frequencies and percentages were calculated for categorical and multiple-response variables, while means (M) and standard deviations (SD) were calculated for the five-point Likert items. Findings were organised according to the five research questions so that the results could inform the selection of tools, institutional support measures, pedagogical integration models, impact indicators, and risk-mitigation strategies for GenAI-enhanced assessment and feedback. No inferential tests were conducted at this exploratory stage. Because convenience sampling was used, educator-student differences are interpreted descriptively and are not presented as statistically generalisable group effects. All reported quantitative findings derive exclusively from the educator (n = 61) and student (n = 254) survey datasets held in the project record.

D. Methodological Limitations

The use of convenience sampling limits the generalisability of the findings beyond the participating respondents, the wider MUA community, and other institutional contexts. The results should therefore be interpreted as an institutional baseline for the design and piloting of GenAI-supported assessment and feedback practices rather than as representative estimates of higher education as a whole.

Furthermore, the research uses self-reporting data that might be subject to distortion due to memory lapses and social desirability bias, especially when students report their experiences with GenAI use in graded assessments and other academic activities. Furthermore, due to its descriptive nature, the design is not able to show how the application of GenAI contributes to feedback quality, learning, and assessment validity.

IV. FINDINGS

A. RQ1 — What GenAI Tools Can Be Integrated?

From the findings, GenAI-enabled assessment and feedback at MUA seems to be carried out via a diverse range of platforms. ChatGPT appears to be the most common generative platform among both students and instructors, whereas the differences between the two groups are seen more clearly on the Turnitin platform.

1) Most frequently used GenAI tools: The distribution of the most frequently used GenAI tools is reported in Table II and visualised in Fig. 1.

TABLE II. MOST FREQUENTLY USED GENAI TOOLS (% OF RESPONDENTS, MULTI-SELECT; EDUCATORS N = 61, STUDENTS N = 254)

Tool	Educators (n = 61)	Students (n = 254)
ChatGPT	78.7%	83.1%
Gemini (Google)	36.1%	41.3%
Turnitin	47.5%	4.7%
Claude.ai	31.1%	16.1%
Microsoft Copilot	24.6%	17.7%
DeepSeek	9.8%	8.7%
Grok (xAI)	6.6%	9.1%
NotebookLM	11.5%	—
Perplexity	1.6%	5.5%

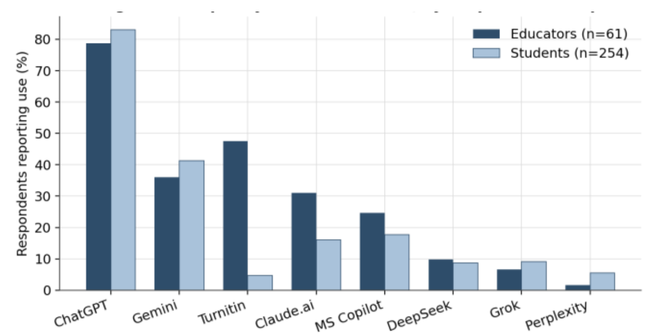

Fig. 1. Generative AI tool use frequency, by respondent group (% of respondents selecting each tool; multi-select; educators n = 61, students n = 254).

In aggregate, the tool use pattern reflects a complementary system of assessment. While conversational systems like ChatGPT, Gemini, Claude.ai, and Microsoft Copilot are mostly employed to assist in ideation, explanation, drafting, and formative feedback, Turnitin is primarily utilised for integrity checks and assessment validation purposes. Hence, the practical recommendation would be that institutional adoption of the tools should not revolve around one particular system but rather should include the combination of generative assistance with transparency, verification, and academic judgment by humans. Indeed, this practice corresponds to the international findings of ChatGPT being the leading point of entry into GenAI-based learning and assessment [8].

2) Technologies that are currently integrated/permitted for assessment and feedback: For the educators, the technologies integrated or permitted for use were listed as: Turnitin (42.6%), ChatGPT (32.8%), "None – not yet permitted" (16.4%), Gemini (14.8%), and Claude.ai (11.5%). For the students, there is confusion: "I don't know" (45.7%), "ChatGPT/Copilot" (23.2%), "No specific technology" (22.8%), and "Turnitin AI detector" (4.7%).

While on one hand, there is the difference between the 16.4% who stated that the use of GenAI tools is not allowed, and on the other hand, the 45.7% who don't even know what can be used; there is definitely some kind of gap in terms of governance and communication for conducting assessments [9]. There have been instances of informal use, but the parameters of allowed use have not been well known to the students. As a matter of fact, until the use of GenAI becomes part of the assessment and feedback process, MUA must define what is allowed and the consequences of using it.

B. RQ2 — What Do Educators and Students Need for GenAI Integration?

The ninth item (Likert Scale 1 to 5, where 1 represents strongly disagree and 5 represents strongly agree) was employed to determine the requirements for responsible GenAI-driven assessment and feedback.

1) Educators (n = 61): Educators' institutional and training needs are summarised in Table III, and the corresponding mean scores with standard deviations are shown in Fig. 2.

TABLE III. EDUCATORS' PERCEIVED INSTITUTIONAL AND TRAINING NEEDS (ITEM 9, 1–5 LIKERT SCALE, N = 61)

Statement	M	SD	N
The university should provide institutional access (premium licence) to GenAI tools	4.34	0.93	61
Using GenAI requires redesigning assessment methods (process-based, not only final product)	4.05	1.01	61
GenAI can substantially improve the quality and speed of feedback	3.98	1.07	61
I need professional training on prompt engineering and GenAI ethics	3.36	1.45	61

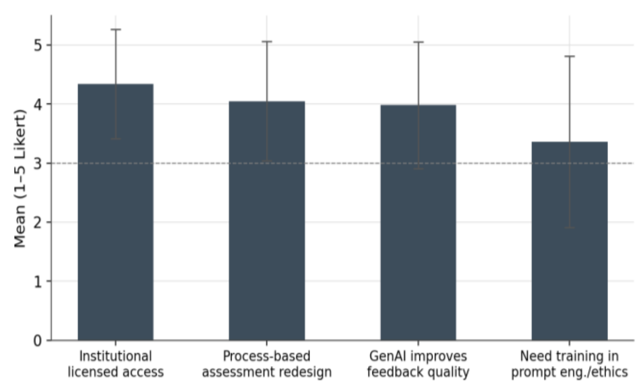

Fig. 2. Educators' perceived institutional and training needs (Item 9), means with standard deviation (1–5 Likert scale; n = 61).

2) Students (n = 254): Students' corresponding institutional and training needs are reported in Table IV.

TABLE IV. STUDENTS' PERCEIVED INSTITUTIONAL AND TRAINING NEEDS (ITEM 9, 1–5 LIKERT SCALE, N = 254)

Statement	M	SD	N
Students and educators need clear guidelines for integrating GenAI without compromising academic integrity	3.41	1.29	254
The university should provide institutional access (licence) to GenAI tools	3.19	1.29	254
I need training on the ethical and safe use of GenAI	2.93	1.36	254
I need faster, more personalised feedback using GenAI	2.82	1.22	254

Institutional access emerges as the strongest enabling condition, particularly among educators (M = 4.34, SD = 0.93), followed by the need to redesign assessment around learning processes rather than final products (M = 4.05, SD = 1.01). Students also prioritise clear guidance for using GenAI without compromising academic integrity (M = 3.41, SD = 1.29). These results indicate that sustainable implementation depends on more than access to technology: it requires coordinated licensing, explicit rules, staff development, and assessment designs that make student reasoning and revision visible. The lower and more dispersed student ratings may reflect their existing reliance on freely available tools outside institutional systems, while educators experience the responsibility for assessment quality, accountability, and data protection more directly [9].

C. RQ3 — How Should GenAI Tools Be Integrated into Pedagogical Practice?

Items 6 and 7 (frequency and activities), together with item 10 (preferred integration models), show how GenAI is currently entering assessment-related work and which role it should occupy in future pedagogical practice.

1) Frequency of use: The frequency patterns for educators and students are presented in Table V.

TABLE V. FREQUENCY OF GENAI USE, BY RESPONDENT GROUP (% OF RESPONDENTS; EDUCATORS N = 61, STUDENTS N = 254)

Educators (n = 61)	%	Students (n = 254)	%
Several times a week	32.8%	Sometimes (3)	40.9%
Several times a month	26.2%	Often (4)	26.4%
Rarely	19.7%	Rarely (2)	19.3%
Every day	14.8%	Almost every day (5)	8.7%
Rarely or never / Never	6.5%	Never (1)	4.7%

2) Main usage activities: The current deployment seems to be more inclined toward actions aimed at preparation, learning, and feedback, and not at the automation of the summative judgment process. Teachers tend to utilize GenAI in such tasks as literature searching and summary writing (67.2%), case study generation (54.1%), data processing (37.7%), and preparation of lectures and seminars (34.4%). Students tend to use GenAI for literature research (56.7%), coursework and projects (52.4%), exam preparation (31.5%), and programming or other technical tasks (around 27.6% in total). Thus, we may say that GenAI operates as a layer of pre-assessment and feedback preparation.

Thus, the findings indicate that GenAI operates as the layer of pre-assessment and feedback preparation.

3) Most preferred integration model: GenAI as a tool for writing and idea generation was the most commonly favored model by both the educators and the students. In the students' responses, 41.3% selected it as a sole answer to the question, while educators preferred it more often as a standalone option or in conjunction with other conditions. Other conditions included human verification, GenAI use outside of assessment situations, and use in groups. This result reveals a preference for the bounded integration model whereby GenAI can be utilized in the process of assessment but only in specific stages and under human supervision.

In summary, the clearest solution to RQ3 can be seen as a human-in-the-loop, process-based approach. GenAI would provide support for the brainstorming, feedback, revision, explanation, and evidentiary stages, while the educators will retain their responsibility for making the final judgment on the students' achievements. The proposed solution reflects the educator preference for the process-based approach to redesigning assessment (M = 4.05) and recent views on assessment as the verification of authentic learning and evaluative judgment, not prohibition of AI use [10], [11].

D. *RQ4 — What Are the Experienced and Desired Impacts of GenAI Tools?*

1) Perceived effects: Perceived effects are reported in Table VI, while the specific positive impacts are ranked in Table VII.

TABLE VI. PERCEIVED EFFECTS OF GENAI (ITEM 13, 1–5 LIKERT SCALE, MEAN [SD])

Statement	Educators M (SD)	Students M (SD)
GenAI has improved my efficiency / academic performance	2.97 (1.22)	2.84 (1.17)
GenAI has helped me save time and be more creative	3.16 (1.34)	3.09 (1.24)
I would like GenAI integrated more into assessment and feedback	3.15 (1.35)	2.83 (1.23)
GenAI has positively influenced students' academic performance (educators only)	2.67 (1.21)	—

2) Specific positive impacts:

TABLE VII. SPECIFIC POSITIVE IMPACTS OF GENAI (ITEM 14, 1–5 LIKERT SCALE, MEANS RANKED HIGHEST FIRST FOR EDUCATORS)

Impact	Educators M	Students M
Better ideas for exercises, assignments, and projects	3.41	2.96
Better understanding of difficult concepts	3.18	3.26
Considerable time savings	2.95	3.37
More personalised feedback	2.62	3.00
Improved student engagement/motivation	2.56	2.87
Development of technical skills (coding, prompting, data)	—	3.01

3) Overall impact assessment: The influence profile is moderate rather than positive all the way through (Table VIII). The educators point to the highest benefits of the technology in terms of developing more creative ideas for exercises, assignments, and projects (M = 3.41), while the students indicate that they gain the most from saving time (M = 3.37) and grasping difficult concepts (M = 3.26). In total, 59.1% of educators and 49.2% of students consider the influence of the technology positive and very positive, although a significant portion of respondents remain neutral. It appears that the first and foremost contribution of the technology comes in the form of formative assessment and feedback functionality—the ability to develop and revise ideas and make processes efficient—rather than substituting for summative assessment or ensuring better grades (Fig. 3) [3], [8].

TABLE VIII. OVERALL PERCEIVED IMPACT OF GENAI (ITEM 16, % OF RESPONDENTS BY CATEGORY)

Category	Educators (n = 61)	Students (n = 254)
Very positive	6.6%	9.4%
Positive	52.5%	39.8%
Neutral	39.3%	43.3%
Negative	1.6%	2.4%
Very negative	0.0%	5.1%

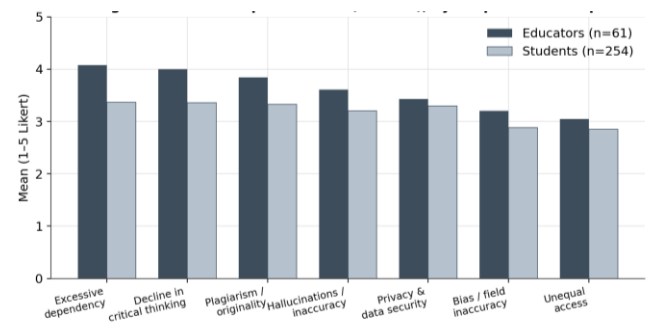

Fig. 3. Overall perceived impact of GenAI (Item 16), share of respondents by category (%; educators n = 61, students n = 254).

E. *RQ5 — What Are the Foreseeable Pitfalls of Using GenAI?*

1) Risk perception: The full risk-perception profile is reported in Table IX and visualised in Fig. 4.

TABLE IX. RISK-PERCEPTION PROFILE (ITEM 15, 1–5 LIKERT SCALE, MEAN [SD], RANKED BY EDUCATOR MEAN)

Risk	Educators M (SD)	Students M (SD)
Excessive dependency on AI	4.08 (1.07)	3.37 (1.31)
Decline in students' critical thinking	4.00 (1.18)	3.36 (1.34)
Plagiarism and lack of originality	3.84 (1.25)	3.33 (1.32)
Inauthentic scientific research	3.74 (1.22)	—
Hallucinations / inaccurate information	3.61 (1.17)	3.20 (1.26)
Projects without sufficient scientific grounding	3.51 (1.30)	—
Privacy and data security	3.43 (1.36)	3.30 (1.26)
Bias/inaccuracy in the specific field	3.20 (1.22)	2.88 (1.25)

Risk	Educators M (SD)	Students M (SD)
Unequal access among students	3.05 (1.38)	2.85 (1.36)
Negative effect on social/emotional development	—	3.07 (1.29)
Decline in the value of the degree	—	2.95 (1.30)

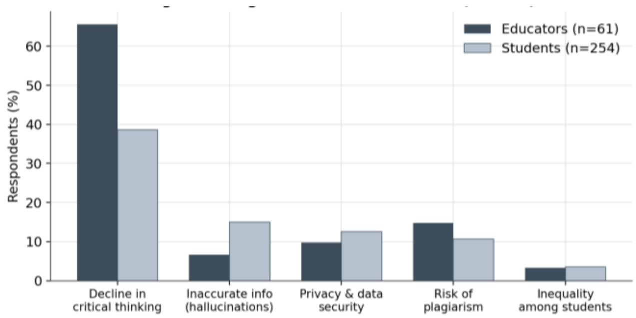

Fig. 4. Risk-perception profile (Item 15), by respondent group (1–5 Likert scale, means; educators n = 61, students n = 254).

2) Main concern: The single most-selected concern is reported in Table X and visualised in Fig. 5.

TABLE X. SINGLE MOST-SELECTED CONCERN REGARDING GENAI INTEGRATION (ITEM 11, % OF RESPONDENTS)

Concern	Educators (n = 61)	Students (n = 254)
Decline in critical-thinking skills	65.6%	38.6%
Inaccurate information (hallucinations)	6.6%	15.0%
Privacy and data security	9.8%	12.6%
Risk of plagiarism	14.8%	10.6%
Inequality among students	3.3%	3.5%

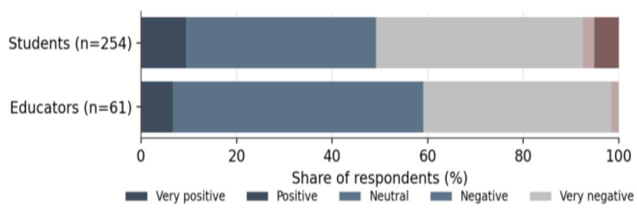

Fig. 5. Single most-selected concern regarding GenAI integration (Item 11), share of respondents by category (%; educators n = 61, students n = 254).

The risk profile makes the challenge of the design of learning and assessment, rather than the mere performance of AI systems, the focus. The most common worry on the list among both teachers (65.6%) and learners (38.6%) is a decrease in critical-thinking skills, while dependence and lack of critical thinking rank first and second in the average mean values of worries among teachers (M = 4.08 and M = 4.00). Plagiarism, hallucinations, privacy, and bias do matter; however, the biggest worry is that wrong design can lead to the deterioration of independent judgment. Therefore, GenAI-enhanced assessment should imply explanation of decisions made, verification of output results, revision of work done, and reasoning of the final outcome. Such a reading is in line with existing literature suggesting that over-dependence and lack of independent judgment can be of greater importance than detection techniques [4], [11].

V. Discussion

It appears that the implementation of GenAI in assessment and feedback should be regarded as pedagogical and institutional change rather than the mere application of new technology. GenAI is currently being applied in activities preceding, during, and after the assessment process, such as exploring relevant literature, generating ideas, preparing assignments, explaining, and revising works. Its educational potential is, thus, mostly associated with the provision of support to formative assessment and feedback loops allowing students to try out their ideas, find weaknesses, and revise their assignments prior to any final evaluation. Such an approach to the analysis of the findings is justified by the feedback-literacy theory that views the successful use of feedback as a learner's active participation in the process of evaluating and improving the quality of their work [1], [2], [10].

In addition, the coexistence of GenAI chat systems and integrity tools confirms that AI-based assessment cannot rely on one tool. ChatGPT, Gemini, Copilot, and Claude.ai assist in generation and explanations, whereas Turnitin is applied to verification and integrity checks. An efficient model of operation in institutions needs to cover generation, feedback, verification, and human decision-making in a transparent process. The problem of uncertainty regarding tools permitted for official use cannot be seen as a mere communication challenge; instead, it is connected to consistency and fairness of decisions. It is crucial to establish clear policies regarding acceptable use of tools by task type, assessment stage, and degree of human control [9], [11], [13].

Institutional access, assessment redesign, and teacher training, three implementation requirements that have been highlighted in the strongest fashion through the study, are interrelated to each other. Although licensed access can facilitate security, accuracy, and equal access to the tool, it doesn't ensure that good education will take place. In order for educators to be able to use the tool well, it is important that they be able to create assignments in which the process of learning becomes observable and assessable. Such process-related evidence, like drafts, prompts, verification, reflection, and explanation, may serve to support good learning assisted by GenAI, rather than mindless outsourcing [9], [10].

Impact findings indicate that at present, the advantages offered by GenAI with regard to efficiency, ideation, and conceptual clarity outweigh those with regard to demonstrable academic achievement. This is significant. While saving time or producing an idea of higher quality might contribute to better learning environments, it is imperative to stress that they should not be considered evidence of any improvements in learning outcomes automatically resulting from such processes. Thus, GenAI-enabled feedback should be assessed not only through efficiency and user experience but also based on its ability to foster awareness of quality, response to feedback, explanation of changes, and transfer of learning – key aspects of feedback literacy [1], [2], [10], [12].

The prevalent threats of dependency, loss of critical thinking, plagiarism, hallucination, and privacy issues point to the importance of assessments that maintain independent thinking and authentic performance. The real issue is not just detection of AI-generated text once submitted; it is making sure that assessments still reflect student knowledge and skills. Possible solutions include sequential assignments, use in specific disciplines, oral or interactive confirmation, documented changes, checking sources, and discussion of GenAI use specifically. Faculty composition might have affected the prevalence of certain GenAI use types, including coding and other technical operations, so further analysis will need to consider this factor. Still, the overall picture clearly shows one path: GenAI should be integrated where it improves formative feedback and learning, but decisions that matter are based on clear criteria and verifiable evidence and human academic judgment [5], [11]–[13].

Descriptively, the MUA pattern is broadly consistent with comparable institution-level studies rather than clearly exceptional. At MUA, 45.7% of students reported not knowing which technologies were officially permitted, whereas Johnston et al. found that 41.1% of students at the University of Liverpool wanted a university-wide policy specifying appropriate use [14]. Likewise, the strong MUA educator rating for institutional access (M = 4.34) and the student emphasis on clear guidance (M = 3.41) align with Kim et al., where approximately 80% of surveyed students and faculty supported formal university policies [16]. MUA respondents also reported moderate rather than uniformly intensive use, which is compatible with Kim et al.'s finding that around 70% of both groups used GenAI less than once per week [16]. These comparisons do not establish statistical equivalence because instruments, samples, and contexts differ; they instead indicate that MUA's governance, guidance, and adoption gaps resemble patterns reported in other higher-education settings.

VI. CONCLUSIONS

This study serves as an institution-level evidence base for the responsible implementation of GenAI in assessment and feedback in higher education. The findings reveal that GenAI is currently being integrated into processes such as ideation, literature exploration, preparation of assignments, explanation, and revision; however, these activities are currently far more developed at the individual-user level rather than the institutional-design level. The challenge now is not whether GenAI would become a part of assessment, but how institutions can incorporate its use to improve feedback and learning while preserving the validity, equity, and transparency of the assessment process.

The study demonstrates support for the process-oriented and human-in-the-loop model of GenAI-enhanced assessment. In this model, GenAI may play a part in formative feedback, clarifying concepts, drafting and revision, and suggesting alternatives, while educators are responsible for learning outcomes, criteria, validation of evidence, and the academic judgment of the work. This is not only an expansion of the debate from yes-no to a design-focused approach but also goes beyond it.

The five research questions can therefore be answered directly. RQ1: ChatGPT is the dominant generative platform, but institutional adoption should combine generative tools with integrity and verification systems rather than rely on a single application. RQ2: The principal prerequisites are licensed institutional access, clear rules, professional development, and process-based assessment redesign. RQ3: GenAI should be integrated through a bounded human-in-the-loop model in which it supports ideation, explanation, feedback, revision, and preparation while educators retain final academic judgment. RQ4: The strongest educational advantages are efficiency, time savings, idea generation, conceptual clarification, and formative feedback, with no evidence in this descriptive design that these benefits automatically translate into improved learning outcomes. RQ5: The main risks are excessive dependency, erosion of critical thinking, plagiarism and originality concerns, hallucinations, privacy and data-security issues, bias, and unequal access; these require governance and assessment designs that preserve independent reasoning and verifiable evidence.

The educational value of the benefits noted in this study is mostly evident in the areas of efficiency, ideation, time savings, and helping understand complex issues. These are highly valued educational benefits but should not be regarded as automatic proofs of better learning outcomes. The value of GenAI-based feedback for education becomes apparent when learners use it critically, check information, justify decisions, and use feedback to improve future performance. Therefore, institutional implementation should include the availability of relevant tools, teacher training, student coaching, guidelines for appropriate usage, and designing assessments to assess genuine knowledge and skills.

Dominant threats of excessive dependence, critical thinking degradation, plagiarism, hallucinations, and data-privacy issues prove that the main difficulty with implementation of GenAI lies in both the technical and pedagogical aspects.

1) Limitations and future directions: However, there are several limitations that need to be taken into account while analysing the findings. First, a limited sampling strategy will not allow for generalisation of the findings to the full population of MUAs or even another university setting. Second, the use of self-reporting for use, benefits, and risks associated with using GenAI tools is associated with problems such as recall bias or even a desire to appear socially desirable, especially when it comes to use and academic integrity. Third, due to its purely descriptive nature, this design cannot help establish causation between GenAI use and learning outcomes, quality of feedback, or assessment results. Finally, the different distribution of academic disciplines among faculty and students could lead to the prominence of some areas such as programming, literature search, or writing assignments.

ETHICAL CONSIDERATIONS

The research was performed under the approval of the Mediterranean University of Albania. This formal approval provided the HEGenAI research group authorization to collect, analyze, and present results obtained through a questionnaire and interview survey of teachers and students at the Mediterranean University of Albania. The approval proves that data were collected in accordance with the rules of this institution and that the research meets the academic integrity requirements of this institution as well as internationally recognized ethical research standards.

Participation was voluntary and based on informed consent. Participants were told the purpose of the study and how their responses would be used before taking part. No personally identifying information was retained in a form that could be traced to an individual: every response used here was depersonalised and anonymised before analysis, so that no educator or student can be identified from the reported results. No fabrication, falsification, or other research misconduct occurred at any stage of the work.

Conflict of Interest and Funding Disclosure

This research was conducted within the Erasmus+ KA220-HED project "HEGenAI – Generative AI for Assessment and Feedback in Higher Education Cooperation" (Grant No. KA220HEDE5871007), co-funded by the European Union. The funder had no role in the design of the study, the collection or analysis of the data, or the decision to submit the manuscript for publication. The authors declare no financial or personal relationships that could have influenced the work reported here.

Authors' Contribution

Following the CRediT taxonomy: D. Hyka: conceptualisation, methodology, formal analysis, data curation, and writing of the original draft. E. Shabanaj: methodology and investigation, with a focus on the AI-related components. J. Meçaj: software and investigation. A. Hykaj: validation and writing (review and editing). E. Skendaj: project administration. All authors read and approved the final version of the manuscript.

Data Availability Statement

The data supporting the findings of this study consist of anonymised questionnaire responses from educators and students of the Mediterranean University of Albania. Because the dataset was collected under an institutional authorisation limited to the HEGenAI project, it is not publicly deposited. The anonymised data may be made available by the corresponding author on reasonable request, subject to the institution's data-protection conditions.

Originality Check

Before submission, the manuscript was screened for originality using Turnitin. The similarity index, excluding references, direct quotations, and bibliographic material, remained below the 20% threshold set by the journal.

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