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Artificial Intelligence, Assessment Redesign and Student Engagement: A Cross-Sectional Survey of Students and Faculty at an Italian University

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Abstract: Assessment and feedback are the main levers through which higher education shapes student engagement, and generative artificial intelligence (AI) is changing how both operate. This cross-sectional case study examines how students and faculty at a public university in Italy position AI in relation to assessment, feedback and learning. Two parallel surveys adapted from the Digital Education Council instruments were administered in spring 2026 to faculty (n = 102; 33% of those invited) and students (n = 440; 8%), while institutional AI guidelines were in force. Analyses are descriptive, benchmarked against the international samples, and complemented by thematic coding of open-ended answers. Students use AI almost universally as an informal formative resource for explanations, self-testing and checking solutions. Those with high or complete trust cite personal verification more often than teacher guidance. Faculty use AI to design assessment tasks but rarely to generate feedback (4% of users); half expect to redesign their assignments, yet only 18% see a need for significant change to assessment (54% internationally). Both groups share concern for students' cognitive autonomy, suggesting that assessment redesign should focus not simply on whether AI is permitted, but on whether its use supports or substitutes the cognitive processes that assessment is intended to elicit.

Keywords: artificial intelligence; assessment and feedback; student engagement

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1. Introduction

Assessment and feedback are central levers of student engagement: they signal what matters, direct learners' effort and sustain self-regulation (Nicol & Macfarlane-Dick, 2006). Generative artificial intelligence (AI) unsettles this relationship by producing competent texts, solutions and explanations with limited visible effort, weakening the link between assessment tasks and evidence of learning. Assessment reform therefore becomes a systemic rather than an individual concern (Lodge et al., 2023), particularly as student adoption has outpaced faculty preparedness and institutional guidance (Digital Education Council, 2024, 2025).

We approach this problem through engagement, understood as behavioural, emotional and cognitive (Fredricks et al., 2004) and as a dynamic state emerging from the interaction between students and institutional practices (Kahu & Nelson,

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2018). Cognitive engagement is most directly at stake: requesting repeated explanations and submitting generated text both constitute AI use, but involve very different levels of effort and agency. In high-school mathematics, unrestricted AI assistance improved supported performance but reduced subsequent unassisted performance, an effect mitigated by tutor-like guardrails (Bastani et al., 2025). In a writing experiment, AI improved students' products without corresponding gains in knowledge transfer (Fan et al., 2025).

Distinguishing productive support from cognitive offloading requires feedback literacy (Carless & Boud, 2018) and evaluative judgement (Tai et al., 2018), now extended to the appraisal of AI output (Bearman et al., 2024). From an assessment perspective, the central problem is validity rather than cheating (Dawson et al., 2024), and rules about permitted use cannot substitute for structural changes to tasks (Corbin et al., 2025).

Recent studies have compared student and faculty perspectives in other national contexts (Kim et al., 2025; Kizilcec et al., 2024), whereas a large Italian multi-institutional study surveyed students only (Farinosi & Melchior, 2025). Building on this literature, the present study examines students and faculty within one Italian public university operating under shared institutional guidelines. The research questions (RQs) are: RQ1, how do students use AI for learning, and what does this imply for self-regulation? RQ2, how do faculty position AI within assessment and feedback, and do they perceive a need for redesign? RQ3, where do the groups converge or diverge on what assessment should protect, and how do their views relate to institutional rules? The surveys do not measure engagement directly, but the conditions under which it may be sustained or undermined.

2. Materials and Methods

2.1. Setting and instruments

This cross-sectional case study involved a public university in central Italy with five Schools. Staff guidelines (July 2024) let instructors define AI policies in course syllabi, recommend prohibiting AI in assessment unless expressly permitted, and prohibit AI evaluation of student work. Student guidelines (January 2026) distinguish uses permitted with disclosure, requiring authorisation, or prohibited, including unauthorised examination use. They require AI-use declarations in theses and commit the institution to AI-literacy training, equitable access to contracted tools and compensatory uses for students with specific learning disorders.

Two parallel questionnaires, available in Italian and English, adapted the structure and core items of the Digital Education Council (DEC) Global AI Faculty Survey 2025 (1,681 respondents in 28 countries) and Global AI Student Survey 2024 (3,839 respondents in 16 countries) (Digital Education Council, 2024, 2025). Each included institution-specific items and three open-ended questions, alongside single-choice, Likert-scale and multiple-choice items. In the student questionnaire, "AI tools" referred to generative assistants such as ChatGPT, Copilot, Gemini and similar tools.

2.2. Procedure and participants

Both surveys were distributed by institutional e-mail to all faculty members and enrolled students, including doctoral students. Faculty responses were collected

from 9 April to 8 May 2026 and student responses from 24 April to 13 June 2026. Participation was voluntary and anonymous, with no incentives.

Only completed and submitted questionnaires were included. Of 124 faculty records, 103 were submitted; excluding one pilot yielded 102 responses (33% of 305 invitees). Of 634 student records, 444 were submitted; excluding four pilots yielded 440 responses (8% of 5,530 invitees). Both samples over-represented the School of Science and Technology (Table 1). Faculty respondents were mainly associate (49%) and full professors (25%). Students were mainly enrolled in bachelor's (55%), single-cycle master's (23%) or master's programmes (20%); 30% were employed.

Table 1. Invited populations, respondents and response rates by School.

School	Faculty invited	Faculty resp.	Faculty RR	Students invited	Students resp.	Students RR
Science and Technology	99	43	43%	1,757	191	11%
Pharmacy and Health Products	53	20	38%	1,163	84	7%
Biosciences and Veterinary Medicine	75	20	27%	1,389	73	5%
Architecture and Design	43	12	28%	772	51	7%
Law	35	7	20%	449	37	8%
Not classifiable	–	–	–	–	4	–
Total	**305**	**102**	**33%**	**5,530**	**440**	**8%**

Note. RR = response rate. Students were assigned to Schools from their declared degree programme (doctoral programmes to the hosting School); doctoral students were included among the invitees. Four answers of "Other" could not be classified.

2.3. Data quality and analysis

No duplicate response vectors, branching inconsistencies or out-of-range values were found. Three types of student data-quality issue were retained for sensitivity analysis: three near-empty submissions, 13 cases of straightlining and eight respondents who reported no AI use but indicated purposes of use. Cumulatively excluding these cases changed the main student estimates by about two percentage points at most. Expanding the faculty sample from the 102 submitted cases to all 110 non-pilot respondents who reached the final survey sections, including eight who did not submit, produced similarly small changes. Neither analysis altered the conclusions.

Analyses were descriptive. Following the DEC convention, agreement combined the top two categories of five-point scales; figures in parentheses report the corresponding DEC values. Alternative bases are stated where applicable: faculty purposes of use were calculated among the 56 AI users, assignment policies among the 98 faculty who selected at least one option, and grounds for trust among the 119 students reporting high or complete trust. The DEC AI in Higher Education Global Survey 2026, covering 45,398 respondents in 35 countries, was used as background only because it reformulated part of the item set (Digital Education Council, 2026).

At least one substantive open-ended response was provided by 54 faculty (53%) and 223 students (51%); totals by question are reported in Section 3.3. A single coder developed categories inductively, allowing multiple codes per response.

Frequencies describe themes among respondents to each question. The authors translated quotations from Italian.

Participation followed informed consent. LimeSurvey, an online survey platform, was configured for anonymous data collection and to prevent responses from being linked to invitation records. The research datasets contained no direct identifiers, and quotations were checked for potentially identifying details.

3. Results

3.1. Students: AI as an informal formative resource

AI use for study was widespread (94%), with 85% reporting at least weekly use (Table 2). Purposes emphasised comprehension and practice, led by information seeking or explanation (86%; DEC: 69%). Other uses included summarising, exam preparation and problem-solving. Drafting, paraphrasing and language checking remained below DEC benchmarks.

Table 2. Student responses and DEC Global AI Student Survey 2024 values (%).

Item	Local (n = 440)	DEC 2024
Usage		
Uses AI tools in study	94	86
Uses AI at least weekly	85	54
Uses AI daily	32	24
Purposes (multiple choice)		
Information seeking or explanation	86	69
Summarising documents or notes	37	33
Exam or quiz preparation	36	–
Solving exercises or problems	29	–
Grammar, spelling or style checking	24	42
Creating a first draft	13	24
Paraphrasing or rewriting	10	28
Assessment and concerns		
Worries about fairness of AI in evaluating student work (n = 435)	56	60
Concern: reliability of AI-generated content	65	51
Concern: deterioration of educational quality	43	27
Dependence (n = 434–435)		
Over-dependence on AI in teaching reduces the value received	75	55
Over-dependence would harm own academic performance	66	52

Note. Agreement items aggregate the top two points of five-point scales. Multiple-choice items do not sum to 100. Dashes mark items without a DEC counterpart.

Open-ended responses (n = 206) described explanation, simplification, tutoring and self-testing (see Section 3.3), alongside checking understanding or solutions

(18). One student illustrated self-regulation: "I force myself to rack my brains before asking […]; I write down everything I have understood about a topic and then use its feedback to confirm, refine or correct my reasoning." Other themes were constant, non-judgemental access (18), compensation for gaps in teaching or materials (17), and support for disability or neurodivergence (6).

Trust was moderate for 64% of students and high or complete for 27%. Among the latter (n = 119), 68% cited verification against reliable sources, 60% past experience and 13% teacher or institutional guidance. Fairness concerns about AI evaluation were reported by 56% (DEC: 60%). Asked what would make AI use at university satisfactory, 45% selected skills training and 23% real-time coursework feedback.

3.2. Faculty: task design, feedback and assessment reform

Current (55%) and anticipated (83%) faculty use were close to DEC benchmarks (61% and 86%; Table 3). AI was viewed mainly as an opportunity by 82% (DEC: 65%), while 95% of users reported minimal, limited or moderate use (88%). Among 56 users, 70% created teaching materials and 45% designed assessment tasks, but only two (4%; DEC: 24%) generated feedback on student work.

Table 3. Faculty responses and DEC Global AI Faculty Survey 2025 values (%).

Item	Local (n = 102)	DEC 2025
Adoption		
Uses AI in teaching	55	61
Expects to use AI in future teaching	83	86
Purposes of use (base: users, n = 56)		
Creating teaching materials	70	75
Designing assessment tasks	45	–
Teaching students to use and evaluate AI	23	50
Boosting student engagement in class	23	45
Tutoring outside class hours	11	–
Generating feedback on student work	4	24
Openness to AI by area (happy to explore or strongly support)		
Creating assignments	60	70
Teaching students to use and evaluate AI in class	70	71
Grading and generating feedback on student work	37	46
Assessment		
Significant or urgent change to assessment methods needed	18	54
Will need to redesign assignments to be more AI-resistant	49	50
AI in assignments (base: n = 98, multiple choice)		
Not permitted	40	23
Permitted with disclosure	24	38
Permitted with disclosure and specific instructions	38	57
Required	4	11
Concerns		
Students' ability to critically evaluate AI output	84	83
Students becoming overly dependent on AI	85	82

Note. Local percentages are rounded to the nearest whole number. Agreement figures aggregate the top two points of five-point scales. Openness items are based on 100–102 valid responses. Multiple-choice responses do not sum to 100%. Dashes indicate items without a DEC counterpart.

Faculty were more open to creating assignments and teaching students to use and evaluate AI than to grading and generating feedback (Table 3). For the latter, 15% were strongly opposed and 25% urged caution. These responses were collected under institutional guidelines prohibiting AI evaluation of student work.

While 49% of faculty expected to redesign assignments to make them more AI-resistant (DEC: 50%), only 18% considered significant or urgent changes to assessment methods necessary (54%), 36 percentage points below DEC. The remaining respondents favoured some updates (39%), minor adjustments (26%) or no change (17%).

Preferences for AI use in assignments were divided (Table 3). Among the 39 respondents selecting prohibition, 18 (46%) already used AI in teaching and 29

(74%) expected to do so. Of the 21 current non-users in this group, nine cited uncertainty about how to use it in teaching.

3.3. What assessment should protect

Cognitive autonomy was a shared concern. Faculty concerns about critical evaluation and over-dependence were close to DEC benchmarks (Table 3), and 81% identified fostering critical thinking as an essential educator skill (DEC: 81%). Open-ended responses mentioned erosion of critical thinking or autonomy more often than assessment integrity (Table 4). One faculty member wrote: "AI generates knowledge but not competence; it is important to teach students not to confuse the two."

Student concerns about over-dependence, content reliability and deterioration of educational quality exceeded DEC benchmarks (Table 2). Open-ended responses also highlighted erosion of reasoning, effort or autonomy and unreliable output (Table 4). One student described dependence directly: "I can no longer make myself read a whole page of my notes without asking ChatGPT to explain it in simple words."

Among valid respondents (faculty n = 98–101; students n = 433–435), 27% of faculty reported knowing the staff guidelines and 14% of students reported full awareness of university AI rules. Guidelines were considered comprehensive by 27% of faculty and 13% of students; 51% in each group were neutral. Training was mentioned more often than guidelines in both groups' open-ended responses (Table 4). Among 434 students, 62% wanted involvement in AI-related decisions (DEC: 71%), while 41% expected increased AI use in teaching (59%).

Table 4. Selected themes in the open-ended answers (number of respondents).

Question	Faculty	Students
How AI is most useful (faculty n = 49; students n = 206)		
Producing teaching materials / explanation of unclear content	21	77
Creating assessment or self-assessment items / self-testing	10	20
Simplifying content to own level	–	34
AI framed as a personal tutor	–	21
Reports no use or no usefulness	8	7
Main concerns (faculty n = 48; students n = 199)		
Erosion of critical thinking, reasoning or autonomy	28	59
Unreliable or incorrect output	2	50
Assessment integrity / unfair advantage	5	6
Priorities for the university (faculty n = 51; students n = 178)		
Training (faculty and/or students)	34	69
Access to tools and licences	21	13
Clear policies and guidelines	9	7
Rejects or limits institutional action on AI	2	7

Note. Exploratory single-coder analysis; responses could receive more than one code. In paired labels separated by a slash, the faculty label appears first.

4. Discussion

4.1. Informal AI feedback and self-regulation

Students' reported use of AI for explanations, self-testing and checking solutions suggests an informal feedback process. Comparing one's own reasoning with AI responses can be interpreted as internal feedback generation (Nicol, 2021), consistent with self-regulation principles (Nicol & Macfarlane-Dick, 2006). Accounts of reflective use and dependence illustrate the tension between scaffolding and cognitive offloading, also highlighted by experimental research (Bastani et al., 2025; Fan et al., 2025). These reports do not establish learning effects, teachers' involvement or how such practices relate to formal assessment.

Assessment design could make these practices explicit through declared AI-assisted drafts with reflections on accepted, corrected or rejected suggestions, or critiques of AI output against explicit criteria. Such tasks could develop feedback literacy (Carless & Boud, 2018) and evaluative judgement (Bearman et al., 2024; Tai et al., 2018). In an Italian study combining rubric construction, exemplars, AI-supported revision and self-assessment, students reported stronger reflective and criterion-based dispositions, although the single-group design does not establish causal effects (Doria et al., 2026). Our findings suggest that students are developing learner-initiated feedback practices around AI that may operate partly outside formal pedagogical mediation: those reporting high or complete trust cited personal verification far more often than teacher or institutional guidance. Assessment design could bring these practices into structured activities in which teachers explicitly mediate criteria, verification and reflection. These proposals were not tested in the present study.

4.2. Assignment redesign and perceived need for assessment reform

Compared with DEC, the gap was one percentage point for anticipated assignment redesign but 36 for perceived need for major assessment reform. Three untested explanations are plausible: confidence in oral examinations, policies centred on course-level permissions, and a tendency to treat cognitive risks as learning rather than assessment issues. These findings suggest designing tasks that make reasoning visible, prioritise validity (Dawson et al., 2024) and translate AI-use rules into assessment practice (Corbin et al., 2025).

The faculty pattern also suggests a distinction between AI adoption and pedagogical integration. Use concentrated on teacher-facing preparation (teaching materials, assessment tasks), whereas learner-facing practices (teaching students to evaluate AI, boosting engagement, generating feedback) were less frequent. The survey does not measure the quality of these practices, but this distribution cautions against equating AI uptake with transformed teaching. Together with the gap between anticipated assignment redesign and perceived need for assessment reform, it may indicate that task-level adaptation is outpacing a systemic reconsideration of assessment.

Only 4% of AI-using faculty generated feedback on student work; the survey cannot establish whether institutional restrictions explain this. Escalante et al. (2023) detected no difference in learning outcomes between AI and human feedback and recommended a blended approach. Grion et al. (2026) also found improved project performance across AI and human feedback conditions, supporting further

investigation of supervised formative uses. Policies should distinguish such support from delegating evaluative decisions to AI.

4.3. Toward shared stewardship of assessment

Shared concern for cognitive autonomy offers common ground for assessment redesign. This convergence shifts the issue from academic integrity alone to the quality of the cognitive work that assessment elicits. Cognitive autonomy can therefore serve as a criterion for redesign: the question is not simply whether AI use is permitted, but whether it supports or substitutes the reasoning, judgement and self-regulation that a task is intended to make visible. We propose shared stewardship of AI in assessment: explicit course-level conditions, negotiated where appropriate; revision, self-assessment and reflection under clear criteria and teacher oversight; and student participation in decisions. This participatory dimension is consistent with staff–student partnership approaches to assessment that emphasise student agency and assessment literacy (Deeley & Bovill, 2017). Williams and Ingle (2025) illustrate this approach through student–staff co-design of criteria for evaluating AI-generated responses to assessment tasks. The 62% seeking involvement in AI-related decisions indicates interest in participation; endorsement of this specific model was not assessed.

As international context, 57% of students in DEC's 2026 survey reported that none, few or some instructors clearly explained AI use in assessments. Among AI-using faculty, 35% identified as guides and 35% as gatekeepers, compared with 20% as active adopters (Digital Education Council, 2026).

Operationally, AI use should be disclosed, permitted when supporting comprehension and reflection, and restricted when it substitutes the cognitive process being assessed. Low awareness of local guidelines points to a dissemination need; their implementation in tasks was not measured. More broadly, a European review describes policy development as uneven and predominantly regulatory (Scierri et al., 2026). Existing guidelines, limited awareness and the prominence given to training may therefore point to an implementation gap rather than a purely regulatory one. Faculty development could bridge institutional governance and classroom practice by translating general principles into discipline-specific approaches to task redesign and feedback.

4.4. Limitations

This cross-sectional, single-institution study relies on self-reports and observes neither assessment practices nor learning outcomes; engagement is an interpretive lens rather than a measured construct. Voluntary participation, the 8% student response rate and the over-representation of Science and Technology create risks of selection bias and limit generalisability. Comparisons with DEC are descriptive because populations, periods, wording and language differ, and DEC microdata are unavailable. Student data collection began less than three months after the guidelines were issued, capturing an early stage of dissemination. Open-ended responses were coded by one researcher without reliability estimates, and faculty and student responses could not be linked.

5. Conclusions

Students report using AI as an informal formative resource, while faculty use centres on preparing materials and assessment tasks, with little feedback generation. Anticipated assignment redesign coexists with limited perceived need for major assessment reform. Shared concern for cognitive autonomy and low awareness of institutional guidelines motivate our proposal for shared stewardship: explicit conditions of AI use, teacher oversight and student participation. Training and discipline-specific designs could integrate students' verification and self-testing practices into assessment while preserving the cognitive processes being assessed. Longitudinal research should test whether these approaches support observed engagement and learning outcomes.

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Data Availability Statement: De-identified data underlying the reported quantitative results are available from the corresponding author upon reasonable request. Open-ended responses are not shared to protect participants' anonymity.

Conflicts of Interest: The authors declare no conflict of interest.

Declaration of Generative AI Use: Generative AI tools were used to support language editing, manuscript restructuring and verification of descriptive calculations. All outputs, statistical results, interpretations and citations were reviewed by the authors, who take full responsibility for the final content. Generative AI was not used to generate or alter the survey data.

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