

Ethical Risks and Governance Mechanisms of Generative AI in University Teaching: An Analysis Based on New Institutionalism

Ning Xu^{1*}

¹ Teaching Quality Monitoring Center (Center for Faculty Teaching Development), Taishan University, Tai'an, China

*Correspondence: Ning Xu

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Abstract:

The introduction of generative artificial intelligence into university teaching has made technological risks visible in the misalignment among course rules, assessment methods, and organizational responsibilities. Drawing on new institutionalism in organizational sociology, this article develops an analytical framework of institutional pressures, organizational interpretation, action responses, and risk consequences. The analysis shows that laws and university rules define compliance boundaries, disciplinary communities generate professional norms, and shared understandings among teachers and students shape the actual implementation of rules. Universities may respond through substantive absorption, selective adaptation, or symbolic compliance. The disjunction between institutional texts and course-level practice is a major organizational source of persistent ethical risk. The article therefore proposes task-tiered course rules, process-based learning evidence, data-access controls, position-based responsibilities, and dispute-review procedures as practical arrangements for translating general principles into routine teaching procedures in local universities.

Keywords:

Generative Artificial Intelligence, University Teaching, Ethical Risk, New Institutionalism

1. Research Problem and Analytical Framework

Generative AI has entered lesson preparation, question answering, assignment revision, and learning assessment. Zhang et al. approach this development from the perspective of educational subjectivity and warn that students' cognitive activities may be displaced by generated outputs [1]. Tong and Yang focus on the value choices embedded in technology and emphasize moral constraints in design and use [2]. Wang et al. further propose a risk-management framework covering technology, data, algorithms, and applications [3]. These studies clarify the subjects, sources, and categories of risk, but they explain less adequately why a university-level rule may be enacted differently across departments and courses.

International studies also differ in emphasis. Dabis and Csáki examine early policy responses by higher education institutions and find that academic integrity and data

protection entered institutional texts first [4]. Bacalso et al. synthesize recent institutional practices and emphasize the influence of governance maturity, cross-departmental coordination, and continuous evaluation on implementation outcomes [5]. These differences indicate that risk lists and policy clauses capture only part of governance; how organizations interpret and enact external requirements also requires analysis.

New institutionalism in organizational sociology examines organizational action under legitimacy pressures. This article distinguishes regulative, normative, and cultural-cognitive sources of pressure, and then examines how universities translate them into university rules, departmental arrangements, and course requirements. Organizational responses include substantive absorption, selective adaptation, and symbolic compliance. Substantive absorption means that rules enter teaching design and assessment procedures; selective adaptation reflects disciplinary differences; symbolic compliance appears when institutional texts are complete but course boundaries remain ambiguous. This logic constitutes the analytical pathway of the article.

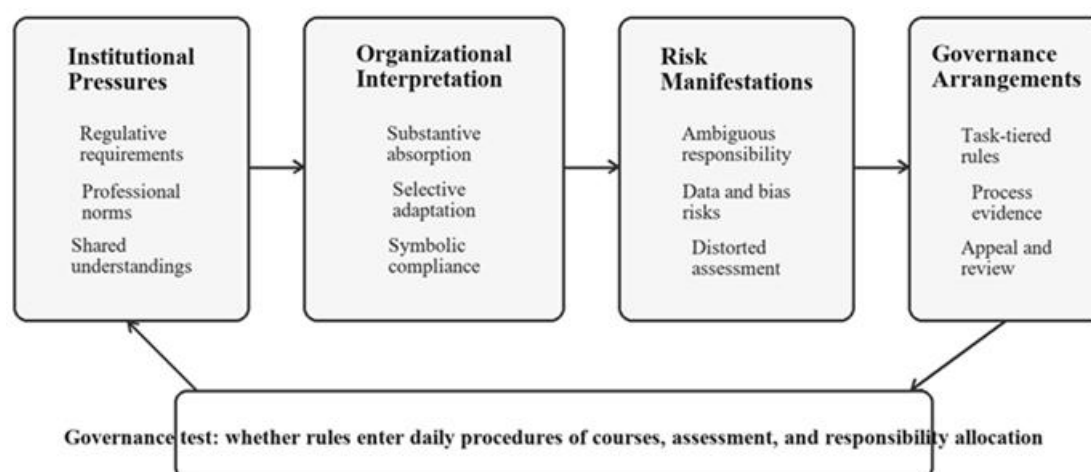


Figure 1. An institutional analytical framework for the governance of generative AI in teaching.

2. Scenarios of Ethical Risk in Teaching

2.1. Learning Support: Cognitive Engagement Displaced by Generated Outputs

Models can rapidly provide conceptual explanations, writing outlines, and answers. If students bypass problem decomposition, source verification, and argumentative reasoning, the apparent completeness of submitted work may increase while conceptual understanding does not. Such judgments should not rely merely on whether a text bears traces of AI use. More important evidence is whether students can reconstruct reasoning, identify sources, and transfer relevant concepts to new situations.

2.2. Assignments and Papers: Ambiguous Boundaries of Intellectual Contribution

Generated content weakens teachers' ability to infer ghostwriting from linguistic style. If a course has not clarified permissible uses, disclosure methods, and prohibited practices in advance, students may find it difficult to distinguish resource assistance, language editing, and substantive ghostwriting. Bittle and El-Gayar treat transparent disclosure, assessment redesign, and student responsibility as interconnected issues

[6]. Gallent-Torres et al. place stronger emphasis on the joint role of teachers and institutions in maintaining academic integrity [7]. Both approaches shift the object of judgment from the tool itself to whether students retain the principal intellectual contribution.

2.3. Teaching Data: Convenient Use May Exceed the Scope of Authorization

When teachers upload assignments, classroom recordings, or assessment materials to public models, personal information and unpublished materials may be exposed. Students may also enter identifiable personal experiences during continuous dialogue. Individual teachers cannot independently verify a platform's rules for data retention, secondary training, and cross-border processing. Platform access and data classification are therefore institutional responsibilities at the university level.

2.4. Learning Assessment: Scores and Authentic Competence May Diverge

Differences in model-use experience, payment conditions, and device availability may become new opportunity gaps. More directly, existing assignments may no longer measure the intended competence. If courses continue to rely solely on result-oriented texts, the interpretive validity of scores will decline. Oral explanation, in-class performance, version histories, and authentic tasks can supplement process evidence, but these arrangements must also control student workload.

Table 1. *Teaching scenarios, ethical risks, and verifiable evidence.*

Teaching scenario	Major risks	Suggested evidence
Learning support	Cognitive dependence; misinformation	Reasoning explanation, source verification, transfer tasks
Assignments and papers	Ghostwriting; unclear authorship responsibility	Process versions, disclosure of use, oral defense
Teaching data	Privacy leakage; unauthorized processing	Authorization records, platform terms, data classification
Learning assessment	Invalid competence evidence; unequal opportunities	On-site performance, authentic tasks, equivalent conditions

3. How Institutional Pressures Become Organizational Responses

3.1. Regulatory Pressures Define Bottom Lines but May Produce Textual Compliance

Data security, personal-information protection, and academic norms constitute bottom lines that universities cannot avoid. Regulatory pressures often prompt institutions to issue rules quickly, but quickly produced rules are likely to remain general. When teachers confront student use of models for rewriting assignments, generating code, or analyzing data, they still need to make course-level judgments. The institution may appear complete in form while implementation problems remain at the course level; this is a typical form of symbolic compliance.

3.2. Professional Norms Enable Disciplinary Adaptation

Disciplines differ in their requirements for originality, tool use, and training processes. Programming courses may allow models to assist debugging while requiring students to explain algorithms. Writing courses may treat linguistic expression itself as a core competence. Practice-oriented courses must also ask

whether model suggestions can substitute for field judgment. Shen et al. emphasize that university-level systems, teacher training, and course guidance need to be coordinated [8]. From the perspective of organizational response, disciplinary interpretation by departments and course teams is a necessary form of selective adaptation.

3.3. Shared Understanding Determines Whether Rules Enter Everyday Teaching

If administrators treat frequency of tool use as evidence of digital achievement, teachers may add tools merely to display innovation. If teachers treat all generation as cheating, students may turn to concealed use. Both extremes weaken rule enforceability. Universities need case-based discussions to form shared judgments about which learning activities must be completed by students, which forms of assistance may be disclosed, and which data must not enter external platforms. The more concrete this shared understanding becomes, the more easily institutional rules become stable action.

Table 2. *Institutional pressures, organizational responses, and risk consequences.*

Institutional pressure	Substantive absorption	Selective adaptation	Symbolic compliance and consequences
Laws and university rules	Platforms and data-access procedures are established	Permissions are set according to data sensitivity	Only general principles exist; teachers bear risk individually
Disciplinary and professional norms	Assignments and assessment evidence are redesigned	Permissible use is specified by course goals	Old tasks remain; assessment authenticity declines
Shared understanding	Open discussion produces case-based consensus	Reasonable course differences are retained	Slogans or blanket bans lead to hidden use

4. Governance Mechanisms for Routine Teaching

4.1. Course Rules Should Be Based on Task Tiers

Course leaders should clarify the permissible scope of AI use before teaching begins. Resource retrieval, concept practice, and language proofreading may be classified as low-risk assistance. Tasks that directly measure core course competence should restrict substitution and preserve process evidence. Matters involving official grades, disciplinary decisions, or degree judgments must be decided by teachers or committees. The basis of tiering is the importance of the task to learning outcomes and the sensitivity of the data, not the name of a particular tool.

4.2. Assessment Design Should Preserve Evidence of Learning Processes

Assignment assessment may combine outlines, drafts, source statements, classroom presentations, and follow-up questioning. The amount of process evidence should correspond to course risk and should avoid imposing excessive declaration requirements on all tasks. Teachers may also redesign tasks so that students compare model responses, identify evidentiary gaps, and complete contextual transfer, thereby making judgment competence visible.

4.3. Data Access and Position-Based Responsibility Should Be Designed Together

Universities are responsible for platform catalogues, data systems, and dispute channels. Departments conduct disciplinary case analysis. Course teachers communicate boundaries and review learning evidence. Students disclose use and verify generated content. Platform providers explain data-processing and service risks. Responsibilities must be attached to concrete matters, such as who approves the uploading of classroom recordings, who reviews model-assisted grading results, and where students may appeal.

4.4. Implementation Evidence Should Be Used to Revise Institutions

Governance evaluation may examine rule comprehension, difficulty of teacher implementation, student cognitive engagement, data incidents, and time required for dispute handling. The number of violations reflects only visible events and cannot by itself indicate governance effectiveness. Each academic year, universities may select courses for material review and teacher-student interviews, compare rule design with actual behavior, and then revise guidelines and training cases.

5. Conclusions

The ethical risks of generative AI in teaching are shaped jointly by technological capability, course goals, and organizational institutions. A new-institutionalist perspective reveals the conversion links between policy texts and classroom action. Institutional pressures become organizational interpretations, which then generate substantive absorption, selective adaptation, or symbolic compliance and lead to different risk consequences. For local universities, governance should focus on task-tiered course rules, process evidence, data access, position-based responsibilities, and review procedures. Only when rules enter lesson preparation, assignments, assessment, and dispute handling can they acquire verifiable institutional effectiveness.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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