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Can Artificial Intelligence Replace the University Professor? Teaching, Mentorship, and Academic Judgment in Higher Education

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Background

The prospect that artificial intelligence (AI) could replace university professors depends on whether teaching is reduced to information delivery or understood as a broader academic role. This mini-review synthesizes research on artificial intelligence in higher education, generative language models, tutoring, assessment, mentorship, and institutional governance. Evidence shows that AI can perform or accelerate bounded tasks, including explanation generation, practice-question design, routine feedback, and administrative drafting. Carefully designed AI tutoring has produced promising learning outcomes in specific course settings, while other experiments warn that unrestricted assistance can undermine unaided performance or later retention. These studies do not test replacement of the professor's complete work, which also includes curriculum responsibility, disciplinary judgment, student supervision, and accountable decisions. The review therefore treats task substitution as plausible within defined settings, while the prospect of occupational replacement remains unproven. It concludes that universities should evaluate AI as a supervised instructional resource, preserve meaningful faculty authority, and measure learning, equity, trust, and workload before expanding deployment.

Keywords: Artificial Intelligence; Higher Education; Generative AI; Teaching; Mentorship; Academic Judgment

Introduction

The debate over whether artificial intelligence can replace university professors has intensified as generative systems produce fluent explanations, answer subject-specific questions, and assist with assessment. Research on artificial intelligence (AI) in education, however, has consistently documented technologies that support specific processes without replacing the academic profession as a whole. Early reviews of AI in higher education (AIHE) found many publications on profiling, prediction, assessment, and adaptive systems, but relatively few studies of educators' perspectives and pedagogical contexts [1-4]. Recent research on generative AI has expanded the conversation, but the central problem remains unresolved: demonstrating task performance is not equivalent to fulfilling the professor's entire role [5-9]. This distinction matters because professors do more than present information: they set learning objectives, sequence student activities, evaluate work, provide consequential feedback, mentor students, guide inquiry, and uphold academic standards. AI may directly assist with some tasks and indirectly change others, but most studies do not evaluate this combination of responsibilities. Initial surveys and preliminary studies of student reports indicate both perceived benefits and concerns about reliability, authorship, academic integrity, and dependence [9,10]. This mini-review presents a focused narrative synthesis of peer-reviewed research and institutional guidance on university teaching, assessment, mentorship, and AI governance. The review does not claim an exhaustive search or pooled effect estimates, and evidence from K–12 education is treated as informative but not directly transferable to higher education. The central argument is that AI may substitute for bounded tasks in specified contexts, while evidence for replacing the profession remains weak because current studies do not assess the professor's integrated, accountable academic role. The review takes a functional approach to this question rather than speculating about distant labor-market futures. Other studies model occupational exposure to automation based on assumptions about future software capabilities, organizational adaptation, and job redesign. Here, we analyze what current peer-reviewed evidence reveals about the performance of teaching tasks and the allocation of

academic accountability. Even when an AI system performs a bounded task successfully, the instructor must define the task, interpret the output, and remain accountable to students for resulting decisions. These necessary boundary activities remain part of academic work even when AI performance metrics do not capture them. Furthermore, the evidence base remains uneven across topics and study designs, particularly between established tutoring research and recent generative-AI studies. Much of the generative-AI literature consists of conceptual analyses, descriptive surveys, or small experiments conducted soon after public chatbots became widely available. Reviews of earlier educational AI likewise found recurring application patterns and limited research focused on educators [1-3]. The analysis is calibrated to the available evidence: experimental findings are reported within their studied contexts, while policy guidance is treated as informed extrapolation rather than evidence of outcomes. Rapid changes in technology and policy limit how long the findings of this review will remain current. A published trial may evaluate a chatbot, model, or safeguards that differ from current commercial products, while university policies describe intentions rather than observed classroom experiences. The review prioritizes findings relevant to faculty perspectives rather than providing an exhaustive inventory of education-technology publications. We interpret the conclusions cautiously, recognizing that future studies may strengthen or qualify the current evidence in this rapidly changing area. However, a meaningful assessment is possible: current evidence supports AI's capacity to perform bounded tasks but falls far short of demonstrating replacement of the academic profession.

What "replacement" means in university teaching

Discussions of replacement often assume that one system either can teach or cannot, overlooking the varied structure, context, and consequences of academic tasks. A language model can produce an outline or translation quickly, but speed does not show that it can identify what a cohort has not understood or when a curriculum should change. The professor's role includes interpreting evidence, connecting ideas across a discipline, and adapting instruction to student work and institutional objectives. A more useful comparison distinguishes task automation, augmentation, and occupational replacement rather than comparing AI with an idealized teacher. Automation transfers a defined task to a system, augmentation changes how a person performs it, and replacement would require the system to assume the occupation's linked responsibilities, authority, and accountability. Research on educational tools has often focused on accuracy or efficacy without identifying who retains authority when outputs are wrong, biased, or misaligned with a course [1-4,11-13]. A tool's success or failure on one task cannot establish role replacement because responsibility for errors remains unresolved. The relevant question is which teaching tasks can be transferred without weakening learning or obscuring academic accountability. Explanation, translation, retrieval practice, and routine clarification are relatively bounded tasks, while curriculum design, interpretation of ambiguous work, and consequential course decisions depend more heavily on disciplinary context and accountability [1-4,11-13]. This task-oriented perspective also recognizes that a tool's practical value depends on the wider institutional setting. The relevant comparison may involve teaching assistants, peer instruction, smaller classes, or human tutoring, depending on the task and available institutional resources. Prior work has sometimes relied on fixed scores to estimate replacement potential, comparing a system with no instruction rather than accounting for the activity's function and stakes. Disciplines also differ in how clearly procedures are defined and whether AI serves as modest support or a more disruptive intervention. In a course with clearly defined procedures, an AI system may provide additional practice or help students check their work. In a course involving ambiguous evidence or interpretive debates, instructors help students compare sources, understand scholarly disagreements, and defend arguments under questioning. In professional fields such as medicine, architecture, and engineering, clinical, laboratory, or field learning may make appropriate AI uses less clearly defined. Evaluation should therefore be specific to both the discipline and task under consideration, rather than relying on generic performance measures.

Instruction and tutoring: promising performance, limited scope

Generative AI can provide explanations outside scheduled contact hours and generate alternative examples, practice questions, and summaries at low marginal cost. Reviews describe potential benefits for personalization and access, while emphasizing risks involving fabricated content, bias, privacy, and dependence on generated output [5-9]. These possibilities make AI a useful instructional resource when a professor defines the learning objective, selects appropriate materials, and asks students to verify explanations against reliable sources. Controlled research offers a more nuanced picture: in a randomized undergraduate physics study, a carefully designed AI tutor produced greater learning gains than an active-learning classroom condition across the measured lessons, and participants rated its explanations favorably [14]. This result shows that a pedagogically constrained tutor can support learning in a specific setting, but it does not compare AI with a professor across a full course, research supervision, advising, course design, or unforeseen student needs. Earlier research on intelligent tutoring systems indicates that structured tutoring can improve outcomes, although effect sizes depend on the system, instructional comparison, subject, and outcome measure [15-17]. Bloom's widely cited two-sigma finding concerned individualized human tutoring relative to conventional group instruction, not AI systems [18]. This distinction matters because an adaptive practice tool and a university professor serve different educational roles. Learning outcomes can decline when students use generative

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tools to obtain answers without practicing the reasoning needed for transfer. A randomized field experiment in high-school mathematics found that access to GPT-4 improved performance while the tool was available but reduced performance on later unaided assessments, whereas a tutor with safeguards mitigated this effect [19]. Although the population and subject differ from university courses, this finding illustrates why immediate task completion cannot substitute for measures of durable learning [19]. In course design, this evidence supports distinguishing practice activities from demonstrations of independent mastery within university teaching. Students may use an AI tutor during low-stakes practice, then complete a task without AI assistance so that supported performance and retained knowledge are both visible. Instructors can ask students to critique a generated explanation, identify unstated assumptions, or compare its claims with a primary source. This approach makes verification part of learning and gives instructors evidence of students' reasoning rather than answer selection alone. Access and equity also require attention when universities introduce AI support into teaching and student learning. Conversational systems may help students who need repeated explanations, language support, or flexible study hours, but usability depends on accessibility, language quality, reliable connectivity, and curricular fit. Models evaluated mainly in dominant languages may perform inconsistently for multilingual cohorts or courses involving specialized terminology. Instructors should check examples against course content and provide alternatives when an AI support tool is inaccessible or unsuitable for students. The design of the tutoring interaction can influence learning as much as the underlying language model. A general-purpose chatbot optimized for quick answers may encourage acceptance of solutions, whereas a tutor can ask diagnostic questions and offer graduated hints before revealing answers. This scaffolding reflects a pedagogical design choice rather than an inherent feature of a capable model. Instructors need to inspect and revise these interaction strategies, while studies should describe prompts, safeguards, and instructional supports clearly enough to enable meaningful comparisons. Evidence of benefit must also be interpreted in light of the retention interval and outcome measure used in each study. A quiz immediately after a lesson measures something different from retention several weeks later, transfer to an unfamiliar problem, or the ability to explain why a process works. Student satisfaction reflects usability, but it does not establish whether learning transfers to new tasks or later assessments. Experiments should report the population, duration, comparison condition, instructor role, and test conditions, including whether students could use AI during testing, to distinguish instructional support from answer generation. Recognizing when an apparent error can advance learning is an important teaching skill during live classroom discussion. A learner may offer an incomplete explanation that reveals a promising hypothesis, a shared misconception, or a connection to material the class has not yet covered. A system designed to produce polished answers may end a discussion before the instructor can identify what students understand or misunderstand. Instructors decide when to clarify a point, ask another question, or invite students to compare competing ideas. An AI system can contribute examples or questions, but instructors should check whether it supports dialogue or narrows discussion to quick answers.

Assessment and Academic Judgment

Assessment is a visible area for task substitution because AI can draft questions, summarize submissions, and generate feedback at scale. These forms of support may reduce the time required to provide feedback, but assessment also involves setting criteria, interpreting disciplinary reasoning, and judging evidence in student work. Studies of university assessment practices report that ChatGPT's ability to answer take-home examination prompts has prompted changes in assessment design and concerns about whether submitted work reliably demonstrates learning [20-22]. Automated feedback can help with repetitive tasks and explicit standards, but confident language may conceal errors or overlook the reasoning behind an unusual answer. A teacher can ask follow-up questions, compare a student's work across activities, and account for approved accommodations or course context; an AI-generated draft may assist with feedback, but the teacher remains responsible for checking accuracy and making consequential judgments. These responsibilities favor assessment designs that reveal students' reasoning through staged assignments, oral explanations, supervised problem-solving, or reflection on tool use. The aim is to align assessment evidence with the intended competence rather than to make every assessment impossible to automate. AI may support practice and formative feedback, while summative decisions require transparent criteria, human review, and a route for students to challenge consequential errors. The European Union AI Act classifies certain educational uses, including some systems that evaluate learning outcomes or affect access to education, as high-risk applications [23]. Another validity concern is that an assessment may measure access to tools, prompting skill, or willingness to disclose AI use rather than the intended disciplinary competence. Conversely, banning every tool may create an artificial assessment condition when graduates are expected to use AI critically in professional settings. Course teams should state which activities require unaided work, which permit AI assistance, and what forms of disclosure students should provide. Clear rules reduce uncertainty and make misconduct procedures more consistent; institutions should retain records of the rubric, the tool's role, and the human review of its output. Students should receive an explanation when automated assistance materially shapes feedback or a decision, and they should have a practical route to request reconsideration. This safeguard matters for students whose writing styles, language backgrounds, or disability-related communication may be misread by automated systems. Instructors must design valid assessments and correct foreseeable errors; AI-detection scores should be treated only as uncertain signals. An AI-detection score

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may be treated as evidence of authorship even when its method is unclear, leaving students with little information to challenge the signal. If concerns arise, the instructor can review drafts and source notes or discuss the work with the student, applying the same published standards across the class. These procedures align with the principle that misconduct findings should rest on evidence rather than probabilistic signals. Feedback quality also requires evaluation because students can act on comments more effectively when revisions are specific and their purpose is clear. An automated response may be relevant yet lack context or overlook requirements specified in the course rubric. A pilot can assess whether students use feedback to improve later work, whether comments accurately identify strengths and weaknesses, and whether student groups receive comparable guidance. Faculty can use identified output errors to improve feedback rules and decide whether a tool should remain limited to formative use or be withdrawn. Assignment instructions can state permitted uses, prohibit generated text in specified sections, and ask students to disclose material assistance in a brief process note. The appropriate rule depends on the learning outcome: a language task may require unaided writing, while research skills may include evaluating AI-generated evidence. Course teams can communicate expectations consistently without imposing a universal prohibition on AI use for students and teaching staff alike.

Mentorship, Research Supervision, and Academic Relationships

Academic relationships develop over time and often require sustained contact between university students and faculty members. A student will ask for guidance on research questions, disciplinary norms, career decisions, and setbacks that cannot be adequately covered in a single prompt. Research on mentoring identifies psychosocial support, role modeling, and academic development as recurring functions, although practices vary across higher education contexts [24,25]. AI can provide general information or help students prepare for a conversation, but it cannot by itself establish a reciprocal mentoring relationship. Human presence should not be assumed to guarantee effective mentoring because students may encounter dismissive feedback, inaccessible instructors, or neglectful supervision. Research on social presence in online learning links perceived presence with satisfaction and learning, while the Community of Inquiry framework defines teaching presence through design, facilitation, and direction [26,27]. These findings suggest that relationships can be mediated by technology, but they do not establish that a conversational system provides human continuity, responsibility, or shared institutional context. In research supervision, AI can help students refine search terms, organize notes, test code, or improve prose, provided they disclose relevant use and verify outputs. A professor remains responsible for research design, ethical approval, interpretation of uncertain evidence, and authorship decisions. A practical near-term arrangement is for professors to use AI to extend routine support while retaining responsibility for supervision and academic judgment. This arrangement can help when students face uncertainty about whether to change a research question or abandon an approach. Students may need to weigh incomplete evidence, personal circumstances, and disciplinary standards when considering either decision. An AI tool can list considerations or help prepare questions for a meeting, but it cannot provide the accountable relationship through which advice is contextualized and revisited. Students can raise concerns about inadequate feedback or pressure to use particular tools with a human supervisor. AI may extend access to routine mentoring support without replacing the continuing relationship between a student and supervisor. Voice-enabled tools can help students formulate questions before consultations, review readings or draft abstracts, and rehearse presentations in advance. Faculty can preserve meeting time for interpretation, feedback, and decisions that benefit from direct dialogue rather than quick answers. This arrangement may shift time toward more substantive interactions, but only if universities protect that time rather than using efficiency gains to increase workloads. The interface should not imply that an AI service offers a confidential human relationship; students sometimes disclose sensitive circumstances while asking professors for academic advice. A commercial chatbot may retain or use this information in ways students do not expect, and conversational AI can seem private or caring without providing either assurance. Universities should explain data practices, provide a human contact for sensitive concerns, and clarify that AI is not a counseling or medical service. These limits can protect privacy, clarify the role of the service, and reduce inappropriate disclosure of sensitive information. Continuity gives supervisors an opportunity to notice changes in student performance and follow up, although monitoring many students creates practical demands. Institutions should assign clear advising responsibilities and manageable caseloads, and include sustained student contact in faculty workload plans. AI tools can help students prepare questions for advising meetings, while faculty remain responsible for setting goals and clarifying academic decisions.

Governance and Conditions for Responsible Use

AI systems can produce confident but unsupported statements, reproduce social biases embedded in training data, and offer recommendations whose sources cannot be traced. Research on language models cautions that fluent output does not demonstrate grounded understanding; system behavior also depends on training data, interface design, and deployment context [28]. In educational settings, these limitations can affect trust, access, privacy, assessment validity, and faculty workload across courses and student groups. Human review is only meaningful if instructors are given time, information, and authority to reject output. Institutional guidance increasingly frames educators

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as active users and designers of AI-supported learning when planning and evaluating deployments. UNESCO's generative-AI guidance and teacher competency framework emphasize human agency, privacy, ethics, pedagogy, and professional development; European Commission guidance likewise encourages critical engagement with AI and data [11-13]. The European Union AI Act imposes requirements on certain high-risk educational systems, including some used for admissions, learning-outcome evaluation, or placement; classification depends on intended use [23]. Universities should define course-specific aims before evaluating a system, and they should assess outcomes beyond convenience and user satisfaction. Relevant measures may include delayed learning, independent transfer, feedback accuracy, accessibility, subgroup differences, student trust, faculty workload, and the quality of academic interaction. Evidence from professional writing tasks suggests that generative AI can improve speed and quality in constrained activities, but those findings do not establish equivalent gains in teaching or supervision [29]. Governance should clarify which decisions require faculty authorization, what records must be kept, how students can appeal, and when an institution will take a system offline. Faculty need preparation in AI literacy and task redesign, not only clear instructions about prohibited uses. This approach allows experimentation while reducing the risk that procurement or cost-reduction decisions replace academic judgment with unreviewed automation. Any classroom pilot should establish a baseline and comparison for the immediate task before implementation begins. For instance, when a university pilots AI feedback, it should document turnaround time and workload, then compare them with feedback quality and later independent performance. Results should be analyzed across relevant student groups, with clear procedures for reporting errors and withdrawing an unsuitable system. These steps help distinguish educational improvement from novelty effects or a simple transfer of labor from faculty to students. Institutions should communicate decisions transparently through clear rules and accessible information about procurement and data practices. Relevant questions include whether prompts or student work are retained, whether information may train a model, how accessibility is addressed, and what happens if a product becomes unavailable. University policies should identify permitted uses and prohibited inputs clearly, so instructors are not asked to manage risks they cannot inspect or control. These arrangements may require staff time, but they give faculty greater information and control over risk. Workload effects also require evaluation: routine production may take less time, while checking outputs, answering questions, and documenting decisions may add work. These costs do not necessarily justify avoiding a system, but they remain part of its impact on universities and faculty. If an institution adopts a tool, it should assess how workload shifts and whether saved time supports teaching, research, or mentoring rather than administrative tasks. Faculty need ongoing support because a single session cannot prepare them to assess changes in system behavior, protect student data, set transparent assessment rules, and respond to disputes. Useful support may include discipline-specific examples, adaptable rubrics, a process for reporting system failures, and time for faculty to review results together. Faculty should participate in procurement decisions because instructional design and tool settings can affect students' learning strategies [19]. Equity analysis should consider how AI decisions distribute benefits and burdens, including differences between students who can pay for premium access and those using free versions. Universities should assess platform accessibility and avoid disadvantaging students who use assistive technologies or choose not to use optional AI tools. Institutions can reduce disparities by offering accessible, approved tools where appropriate and clearly explaining available alternatives. Students should also be assured that declining optional AI tools will not disadvantage them in assessment or course participation. Education leaders should examine differences in model access and data practices across student groups while protecting the privacy of students and faculty. Evaluation should report differences in learning and workload across student groups and tool versions, while protecting the privacy of the people involved. Universities should set review dates and criteria for modifying or withdrawing systems, based on evidence about effects on students and faculty. These commitments preserve room for experimentation while discouraging untested automation that increases faculty burdens or risks student welfare.

Conclusion

Current evidence cannot support either categorical claim: that AI will replace university professors as a whole, or that every teaching task requires a human to perform it unaided. Although AI can provide practice, explanations, drafting support, and routine feedback, well-designed tutoring studies have shown promising results only in specific settings. Other studies identify risks to retention, assessment validity, and academic integrity when systems provide answers without instructional safeguards. The key distinction is between automating individual tasks and replacing the integrated academic role performed by a professor. A professor's work combines teaching with curriculum responsibility, assessment judgment, mentorship, research supervision, and institutional accountability. Universities should treat AI as a supervised resource, measure its effects under realistic conditions, retain human accountability for consequential decisions, and base adoption on educational outcomes. The title question should therefore be answered conditionally: AI may automate or reorganize some professor-led activities, but current research does not show that it can assume the professor's integrated responsibilities. The decision is institutional as well as technical: universities determine whether AI improves access and reduces repetitive work, or removes human contact without measuring the educational cost. A responsible institutional response should keep these choices open to scrutiny by faculty

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members and students. For researchers, the next step is carefully specified empirical research on educational work rather than another broad claim about AI's impact on higher education. Multi-course studies could compare tutoring, feedback, or assessment support across subjects and a full term, tracking learning, delayed outcomes, faculty workload, and student experience. Ethnographic studies can analyze how instructors use AI, how students interpret automated guidance, and how participants assess its benefits and trade-offs. Negative and mixed findings are useful because they help institutions identify where systems remain unreliable in practice. Such a research agenda would give universities a stronger basis for deciding which tasks to automate, which to augment, and which should remain under direct human responsibility.

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