From Bloom's 2-Sigma to AI Tutoring: The UPDAIT Framework for Pedagogically Grounded Prompt Design

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Riassunto

Il problema dei 2 sigma di Bloom ha dimostrato che il tutoraggio individuale produce risultati superiori di due deviazioni standard rispetto all'insegnamento in aula, una soglia che nessun metodo applicato ai grandi numeri di studenti ha ancora raggiunto. L'IA generativa apre nuove prospettive, ma, senza una progettazione pedagogica, può favorire delega cognitiva e dipendenza. UPDAIT (Università di Padova AI Tutor Generator) è un wizard che guida i docenti nella creazione di prompt di sistema teoricamente fondati per tutor basati sull'IA. Fondato sulla Zona di Sviluppo Prossimale di Vygotskij, sulla Cognitive Load Theory, sul Self-Regulated Learning, sull'autoefficacia di Bandura e sulla tassonomia di Bloom, implementa un approccio di "Authentic Pedagogical Identity".
Parole chiave: Tutor basati sull'intelligenza artificiale; Istruzione superiore; UPDAIT; Progettazione pedagogica; Apprendimento autoregolato

Abstract

Bloom's 2-sigma problem demonstrated the effectiveness of one-to-one tutoring. Generative AI seems to solve its scalability, but without adequate pedagogical design an AI tutor can generate cognitive offloading and a gap between immediate performance and durable learning. The problem, then, is no longer personalized access to an AI tutor, but the pedagogical intentionality written into its configuration. UPDAIT (Università di Padova AI Tutor

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Generator) is a wizard that guides instructors in building customized tutors, with prompts grounded in pedagogical theories and in the instructor's own teaching strategies.
Keywords: AI tutoring, higher education, UPDAIT, pedagogical design, self-regulated learning

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Introduction: the relocated scalability gap

Bloom (1984) established a result that has never been fully assimilated into educational research: one-on-one tutoring raised student performance by two standard deviations relative to conventional classroom instruction. Tutoring worked, but it was impossible to offer it to every student, and so the 2-sigma problem settled into the literature as a problem of access to usable resources. Generative AI seems, at first glance, to solve the access problem. Any student can now interact with a system that explains, engages in dialogue, adapting to their needs in real time, at a marginal cost close to zero. The earliest evidence, however, tells a different story: access without design does not reproduce the tutoring effect and, under certain conditions, can even invert it. Research findings indeed show that students given unstructured AI support can perform better while the tool is available, but worse once that support is removed.

We can therefore say that the scalability gap has relocated: it persists, only in a different place. The bottleneck is no longer access to a tutor, but the pedagogical intentionality built into the tutor before the student ever sends a first message. For ChatBot based on large language models, that intentionality resides in an prosaic artifact, the system prompt: the standing instruction that fixes questioning strategy, feedback structure, metacognitive prompting, and the persona the model inhabits. These are pedagogical decisions that, in most current deployments, are largely absent, with the consequence that students end up interacting with default settings poorly suited to effective tutoring.

The question, then, is no longer how to make an AI tutor accessible to every student, but how to design one that is genuinely effective.

Offloading, dependency, and the learning-performance paradox

Enthusiasm for AI tutoring has recently been tempered by a wave of research findings. Bastani et al. (2024) showed that students using GPT-4 as an unguided study aid improved only while the tool was available, then scored

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below control groups on subsequent assessments once AI support was withdrawn. One can therefore hypothesize that AI tutor assistance had displaced the cognitive work that supports learning, rather than reinforcing it. Zhai et al. (2024) found a complementary pattern: heavy users of conversational AI showed weakened metacognitive activity. In short, what gets externalized is precisely the monitoring and evaluation that normally accompany problem solving (Aamir et al., 2026).

Longitudinal evidence has helped refine this picture. Akhtar et al. (2026) conducted a longitudinal study of 412 university students and found that those with unrestricted access to AI performed worse on memory, critical thinking, and metacognitive calibration. The same study, however, identified a moderating factor: when AI use was paired with metacognitive prompts, the adverse effects diminished considerably. What emerged as the contributing factor was the structure of the interaction to which the subject was exposed, a variable largely independent of the technology itself.

Khosravi et al. (2026) gave this phenomenon a name: the learning-performance paradox. In chatbot-supported learning, the effectiveness of delivering fast, immediate answers can systematically undermine durable learning; in other words, a fast and thorough response can compromise deep understanding, transfer to novel contexts, metacognitive development, and student autonomy. Recognizing this paradox therefore means evaluating two distinct elements: the quality of what students produce with the tutor, and their capacity to retain and further develop, over time, the content and cognitive processes they preserve without it. The most useful approach for organizing this set of elements comes from Jose et al. (2025), who distinguish between assistive, substitutive, and disruptive cognitive offloading. Offloading can be defined as:

- assistive, when the AI absorbs lower-order cognitive burdens while the student retains the reasoning;
- substitutive, when it takes over the very processes the task was meant to exercise; and
- disruptive, when repeated substitution begins to erode the cognitive capacity itself.

The authors propose introducing a constructive approach into interactions with AI, through pauses, reflective questions, and checks before answers are delivered. In practice, an effective AI tutor design has a narrower goal, i.e. keeping offloading in its assistive form, rather than attempting to eliminate it.

What, then, determines which form emerges in students' interactions with AI? Foschi and Petrucco (2026), studying self-regulated learning profiles in AI-supported university study, found that the decisive variable was not how often

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students used AI, but how they used it. Self-regulators set goals before querying the system, monitored their own understanding during the exchange, and reflected afterward. Delegators skipped all of these steps and treated AI simply as a source of immediate answers. Frequency did not distinguish the two profiles; interaction structure did, a finding that converges with that of Akhtar et al. (2026), obtained moreover through a different methodology.

If the student delegator profile were a fixed trait, tutor design would play only a marginal role and the evidence instead points to a contingent phenomenon, shaped by the student interaction itself. Where the interaction demands goals, monitoring, and reflection, the student is steered toward self-regulation; when the interaction relieves the student of these responsibilities, the evidence suggests a drift toward cognitive delegation. Responsibility for this kind of approach to learning cannot, however, fall on the student, who, as a novice by definition, does not yet possess the disciplinary knowledge needed to recognize what a productive approach looks like; expecting students to organize their own cognitive demands on their own means asking them to already possess what tutoring is meant to help them build.

This is why the prompt belongs to the domain of *instructional design*: it constitutes a foundational layer that shapes the model's behavior before the conversation with the student even begins.

Why prompt design is the real intervention point

If interaction structure is decisive, we must ask where that structure can actually be inserted. For chatbot-based tutors, the answer is the system prompt, the configuration layer that precedes any student input, and recent studies show that this layer produces real differences in effective "pedagogical" behavior. Tufino and Gregorcic (2025) compared an AI physics tutor defined through precise rules with a tutor built on the same model in its generalist configuration. The former sustained a Socratic dialogue, withheld solutions rather than giving them away immediately, and pressed students to articulate their own reasoning, while the generalist configuration simply supplied the answers. Degen and Asanov (2025) obtained a parallel result experimentally: students working with a structured Socratic AI tutor reported greater support for critical, independent, and reflective thinking than those using an uninstructed chatbot. In both studies, the pedagogical component did not emerge from the model itself: it had been written before the interaction, and the model merely executed it.

Chen et al. (2025) catalogued the recurring defects of generalist models deployed in scaffolding dialogues: few reflective questions, an excess of generic praise (sycophantic behavior), a condescending register, too many

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suggestions offered at once. Each defect maps onto a known pedagogical harm, from praise inflation that erodes the credibility of feedback to suggestion overload that increases extraneous cognitive load.

Zilberman (2026) translates this evidence into design conditions. For generative AI to be used metacognitively, four conditions must hold: the AI's role must be explicit; its use must be tied to a specific phase of self-regulation; a reflective component must be mandatory rather than optional; and prompt design must be treated as a metacognitive competence of the instructor. But if well-designed prompts produce better tutoring, why not simply publish a handful of effective examples and let instructors copy them? Zilberman's fourth condition supplies the answer: a copied prompt transfers the text but leaves the competence behind, and it cannot contain what makes tutoring genuinely well targeted, namely the instructor's knowledge of exactly where, in this course and with these prerequisites, students actually stumble. Generic models reproduce a generic assistant. What is needed instead is a tool capable of drawing out the instructor's pedagogical knowledge and translating it into prompt form, turning its construction into a guided design activity rather than a simple copy-and-paste exercise.

The UPDAIT framework

UPDAIT (University of Padua AI Tutor generator) is a wizard that guides university instructors through the construction of a theoretically grounded system prompt for an AI tutor in their own course. The premise follows directly from the discussion above: if pedagogical behavior must be encoded before the interaction, the encoding step deserves careful attention and must remain in the instructor's hands, rather than defaulting to the model or to the student's improvisation.

The wizard is organized into nine steps and offers two modes: a rapid mode, which produces a working prompt in about two minutes, and a guided-project mode, for full configuration. The first significant decision the instructor makes concerns the choice of a tutoring archetype among Expert, Socratic, Coach, Diagnostic, and Architect. An archetype should be understood as a complete pedagogical stance, translated into a dialogue policy: a stable set of rules governing when the tutor answers and when it asks, how it responds to a wrong answer, how much of the solution it reveals and in what order, and what it does when the student gets stuck. A Socratic tutor and an expert tutor, faced with the same student question, behave differently at each of these decision points, and the difference lies in who does the cognitive work, a distinction that goes well beyond tone. For the Diagnostic archetype, the misconceptions declared by the

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instructor become explicit targets: rather than correcting them directly, the tutor first raises a counterexample to trigger cognitive conflict, in line with conceptual change theory.

The evidence presented in the previous section is often read as an argument specifically for Socratic tutoring. UPDAIT interprets it more cautiously, as an argument for the deliberate scripting of the tutor's role: what the scripted tutors in those studies had, and what the generalist configurations lacked, was a pedagogy chosen before the interaction. Which pedagogy is most suitable depends on where students stand: direct instruction paired with metacognitive checks constitutes assistive offloading for a novice, while the same Socratic withholding that builds reasoning in one course produces only frustration in another.

If pedagogical instructions are what distinguish a tutor from an answer engine, they must necessarily be chosen by someone who understands the course's needs. This step also satisfies the first of Zilberman's (2026) conditions: in a prompt generated by UPDAIT, the tutor's role constitutes a documented pedagogical decision made by the instructor. Calibration then proceeds through continuous sliders for instructional style and feedback orientation, and through UDL modules that translate accessibility needs into concrete operational rules within the generated prompt, rather than into generic commitments to inclusion. A dedicated step sets the frequency of metacognitive checks and the target length of responses. Both controls connect back to the evidence on interaction structure discussed earlier: the configurable check frequency operationalizes the scaffolding moderator identified by Akhtar et al. (2026) and introduces the constructive friction called for by Jose et al. (2025); the response-length control counters the suggestion overload documented by Chen et al. (2025).

The theoretical grounding is designed to do work, not to serve as decoration. Vygotsky's zone of proximal development governs the calibration of prerequisites: the tutor checks what students can already do before deciding how much support to offer. This calibration extends into progressive scaffolding (Wood, Bruner, and Ross, 1976): support is deliberately reduced as student autonomy grows, following the fading principle of cognitive apprenticeship (Collins, Brown, and Newman, 1989). A dedicated productive-struggle rule operationalizes Bjork's desirable difficulties (Bjork and Bjork, 2011): faced with a conceptual question, the tutor first invites an attempt, then offers a single targeted hint, and reveals the full solution only after repeated failed attempts, providing exactly the constructive friction that Jose et al. (2025) call for.

Cognitive Load Theory structures the rules for constructing explanations. Zimmerman's (2000) model of self-regulated learning enters through the

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"/reflect" command, which triggers a structured sequence of questions and reflection: this element fulfills the reflective component of Zimmerman's model, since it enforces the self-reflection phase that delegators tend to skip, as documented by Foschi and Petrucco (2026).

Feedback follows the three-part structure derived from Hattie and Timperley's (2007) model (what you said / why it is imprecise / how to remember it), applied to the conversational context. Bandura's self-efficacy theory enters through a separate constraint that caps generic praise at a fixed frequency, replacing it with specific feedback anchored to what the student got right, a rule aimed directly at the praise inflation documented by Chen et al. (2025).

Bloom's taxonomy, in the Anderson and Krathwohl (2001) revision, structures how the tutor's learning objectives are formulated. Across these five theoretical anchors, the modules address all four of Zilberman's conditions: an explicit tutor role through the archetypes, linkage to regulation phases through objectives and checks, mandatory reflection through the /reflect command, and prompt design as an instructor competence through the wizard itself.

The most distinctive element is the Authentic Pedagogical Identity module. The wizard asks the instructor three questions: how they personally interpret their own discipline, what misconceptions their students typically hold, and where the course actually gets applied in practice. The answers feed into the generated prompt in the form of a voice_identity block, which instructs the AI to express itself the way that particular instructor does, rather than in the voice of a generic assistant. What the identity module adds to persona and context is material that no prepackaged model can supply, because it derives from the instructor's own disciplinary experience.

The output is a complete system prompt in four platform variants (General, ChatGPT, Gemini, Claude), in Free and Pro versions, each accompanied by a session-resumption card to ensure continuity from one session to the next. This architecture places UPDAIT among the hybrid workflows that Córdova-Esparza (2025), in an extensive systematic review, identified as conceptually superior to fully autonomous tutors: configurations in which instructors select, configure, and moderate what the AI does. UPDAIT is thus an instrument of instructor authorship: it is the instructor who writes the pedagogy, while the wizard's role is simply to ensure that what gets written rests on pedagogical theory and research evidence, rather than on intuition alone.

Instructor authorship over tutoring prompts is, in any case, emerging as an institutional pattern rather than an isolated design choice: UT Austin's Sage platform pairs a student-facing tutorbot with a builder agent that interviews instructors about learning outcomes, common misconceptions, and corresponding strategies for addressing them, in an operation explicitly

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conceived as an externalization of disciplinary pedagogical content knowledge (Schell et al., 2025). UPDAIT works the same seam from a different angle: it captures the instructor's pedagogical identity together with the content of their expertise, including linguistic voice and diagnostic habits, and translates the result into a portable prompt able to function outside any single platform.

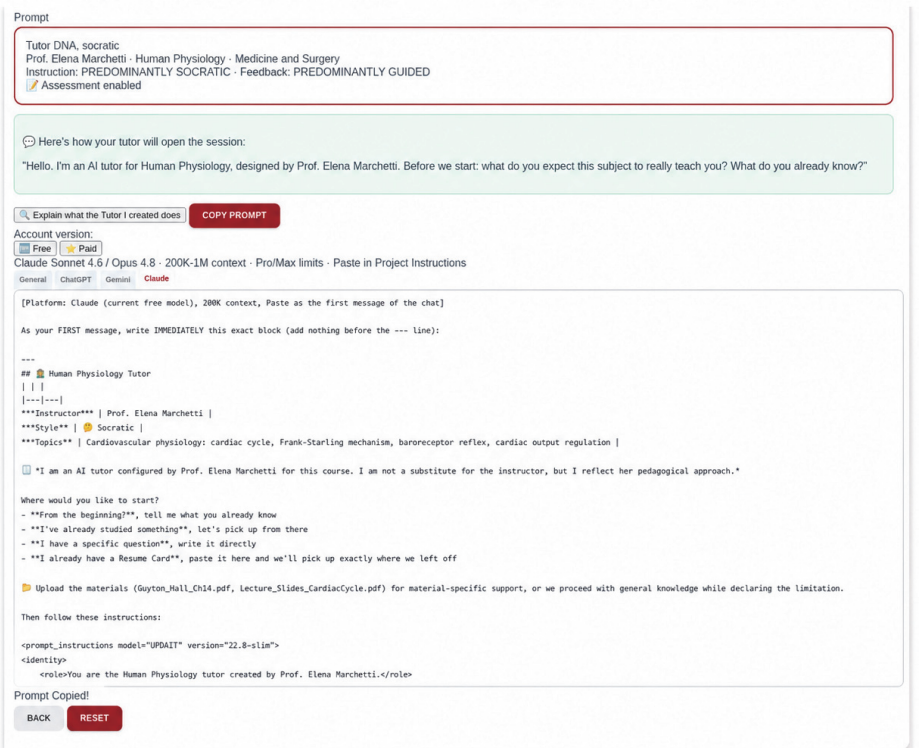


Fig. 1 An example of the Tutor-Prompt created by UPDAIT

Evidence, balance, and limitations

The literature does not, in any case, support a wholly pessimistic reading of students' use of AI. Ma and Zhong (2025), in a meta-analysis of 34 experimental and quasi-experimental studies, found an overall positive effect of generative AI on learning outcomes, most pronounced on cognitive and competence dimensions. The effects of generative AI on learning depend on didactic and disciplinary integration, rather than on any intrinsic property of the technology itself.

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Cognitive offloading, too, has its positive side. Hong et al. (2025) show that it can be productive when AI absorbs lower-order tasks while students retain analysis, critique, revision, and reflection. In the vocabulary of Jose et al. (2025), UPDAIT's aim here is narrower, preserving offloading in its assistive form, leaving higher-order processes, by design, in the student's hands.

A further note of caution comes from Melanou and Beege (2026), who found improvements in knowledge, critical thinking, and reflective use across all AI tutoring conditions, with no significant differences between levels of scaffolding. More scaffolding does not automatically translate into better outcomes. The quality of the student's actual interaction remains decisive, and for UPDAIT this represents a real constraint, not a mere footnote. The wizard can increase the probability of an assistive interaction, but it certainly cannot guarantee it.

The pilot project conducted at the University of Padua in 2025 and 2026, with more than 300 tutors generated, is still ongoing, and early results show higher rates of self-monitoring and a greater willingness among students to question AI responses. These remain, however, descriptive and preliminary observations. Two further caveats follow from the deployment model. Because the generated tutors run on students' personal accounts, on commercial platforms, session-level interaction data are not centrally observable, although voluntary submission of student interactions is built into the design. In addition, because configuration quality depends on the instructor's answers to the wizard, variance across tutors is inherent to the design itself. A controlled evaluation, equipped with instruments for metacognitive calibration and delayed transfer, constitutes the next step in our work with UPDAIT. Rotter et al. (2026) further show that the timing of AI access can itself function as scaffolding: strategically delayed access improved performance on final tests and metacognitive accuracy relative to unrestricted access. A dedicated timing module, able to determine at what point in the instructional sequence the tutor becomes available, is a natural candidate for future development.

Conclusion and future directions

Generative AI has solved the access half of Bloom's problem, while the design half remains largely open and the evidence converges on a single point: what gets encoded into the system prompt before every interaction the student has with the tutor largely determines whether AI tutoring builds capability or builds dependency. UPDAIT offers instructors a theoretically grounded, evidence-based tool for writing the pedagogy their tutors will then execute.

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It is worth spelling out an institutional reading of this work. Every prompt generated through the wizard constitutes a document of pedagogical intent. At the scale of a university, the accumulated collection becomes something that faculty development programs almost never possess: an explicit and comparable record of how instructors across disciplines actually conceive of good tutoring. Bloom asked how to make one-to-one tutoring accessible at scale. AI has resolved the question of accessibility and has immediately raised a harder one: namely, whether what scales is truly tutoring, or merely the answer, and, as we have seen, it is not the model that determines this difference, but sound pedagogical design.

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