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Theoretical and Methodological Foundations of Using Artificial Intelligence Technologies in Teacher Education

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Abstract: Artificial intelligence can assist prospective teachers in producing lesson plans, examples and feedback, but the quality of an assisted product does not establish the quality of the professional learning behind it. This article examines that distinction and develops a methodological framework for AI use in teacher education. A focused literature review brings together technological pedagogical content knowledge, formative feedback, UNESCO guidance and evidence on assisted versus independent performance. The analysis differentiates instructional support, practice simulation and evaluative uses of AI, identifying the professional decisions that should remain visible in each activity. It proposes a learning sequence combining an independent attempt, a bounded AI contribution, verification, pedagogical adaptation and subsequent unaided transfer. Assessment addresses both the revised teaching material and the student teacher's capacity to justify and reproduce relevant decisions without automated assistance. Illustrative tasks and an implementation matrix translate the framework into seminar practice. The results are conceptual and methodological; no original intervention or measured learning gains are reported. The main implication is that AI should be integrated around explicit learning functions, verification procedures and evidence of developing professional autonomy, rather than around the volume or fluency of generated materials.
Keywords: teacher education; artificial intelligence; generative AI; pedagogical judgement; instructional design; formative feedback; professional autonomy; assessment.

Introduction

A prospective teacher may submit a well-structured lesson plan yet be unable to explain why its questions are ordered as they are or how its assessment identifies a misconception. Generative artificial intelligence makes this distinction increasingly consequential. Producing instructional material and learning to make instructional decisions can occur together, but one does not guarantee the other. Teacher education must therefore consider what students learn while using AI, not only what they can produce with it.

The term artificial intelligence covers applications with different functions. Some systems recommend resources, classify responses or adapt a sequence of tasks. Generative systems produce new text and other content in response to an input. A conversational interface does not by itself establish the presence of a valid model of learning. Its responses may be useful, inaccurate, insufficiently contextualised or pedagogically inappropriate. Evaluation should consequently begin with the intended educational function and the evidence available for that function.

The discussion is particularly important in teacher education because the learner is also preparing to make decisions affecting future pupils. An incorrect explanation accepted during training may later enter a classroom. Conversely, a carefully designed activity in which a student identifies and repairs a generated explanation can support professional judgement. The same technology can thus

occupy different positions in the learning process, depending on the task, the required verification and the responsibility retained by the student.

This article asks how AI-supported activities can be organised so that they develop, rather than obscure, prospective teachers' pedagogical reasoning. It examines three related questions: which theoretical perspectives help determine an appropriate instructional role for AI; what sequence of activities keeps the student's decisions observable; and how assessment can distinguish assisted output from developing independent competence. The article offers a conceptual and methodological synthesis, supported by published research and illustrated through proposed seminar tasks.

Theoretical and empirical foundations

Technology integration as a pedagogical decision

Mishra and Koehler's technological pedagogical content knowledge framework places technology in relation to subject knowledge and pedagogy [1]. Its relevance to AI is that tool fluency alone does not constitute an adequate basis for teaching. A generated explanation must be judged against what is being taught, how learners are expected to understand it and what difficulties they may encounter. An output can be grammatically coherent while misrepresenting the concept or demanding knowledge that the learner has not developed.

This perspective suggests a distinction between operating a tool and choosing its instructional role. The first concerns interaction with the system; the second concerns whether its contribution is useful for a specific learning objective. Teacher education should examine both, but the latter is the more important professional decision. Students should be able to explain why an automated contribution is needed and when a simpler resource or a direct discussion would serve the purpose better.

Zawacki-Richter and colleagues' review of AI in higher education highlighted the need for stronger educational involvement and attention to pedagogical and ethical implications [2]. Although the review predates the current wave of widely accessible generative systems, its central question remains relevant to programme design: who defines the educational problem, and which theory connects an application to learning? The review is used here as a historical research perspective, not as a current census of AI applications.

Guidance, feedback and professional responsibility

UNESCO's guidance on generative AI advocates a human-centred approach to education and research [3]. Its teacher competency framework connects AI knowledge with ethics, pedagogy and professional learning [4]. Together, these documents support treating AI competence as more than the ability to compose effective instructions for a system. Understanding limitations and retaining responsibility for a teaching decision are part of the educational objective.

Formative feedback provides another relevant perspective. Hattie and Timperley examine how feedback can inform progress towards a learning goal and the next steps in learning [5]. In an AI-supported task, a response is educationally useful only if the learner can interpret it and act on it appropriately. A detailed comment is not necessarily good feedback, and an immediate answer may remove the very reasoning that the task was intended to develop.

The framework proposed in this article therefore makes response evaluation an explicit student activity. A prospective teacher should identify what a generated suggestion claims, which criterion it addresses and what evidence supports accepting or rejecting it. This requirement transforms feedback from something received into material for professional reasoning. It also makes disagreement with an automated suggestion legitimate where the student provides a sound explanation.

Assisted performance and independent learning

Bastani and colleagues' field experiment in high-school mathematics distinguishes performance during AI-supported practice from performance after access is removed [6]. Their results indicate that unrestricted assistance can produce a different learning outcome from assistance designed around teacher-informed safeguards. This is evidence from a particular educational setting, not a direct estimate of effects in teacher education. The methodological lesson is to examine what remains when assistance is no longer available.

Accordingly, the present article separates three outcomes: the quality of a completed teaching product, the quality of reasoning used to evaluate that product and the ability to make a comparable decision in a new situation. These outcomes may develop at different rates. A programme that measures only the first risks rewarding access to stronger tools or more extensive assistance rather than growth in professional understanding.

Methodology

The study uses a focused narrative review and pedagogical modelling. Sources were selected for their direct relevance to technology integration, AI in education, feedback, teacher competence and responsible educational practice. Foundational work is combined with recent AI guidance and a published field experiment. This is not a systematic review: no comprehensive database screening or statistical synthesis is claimed.

Each source was considered through a common analytical sequence: the educational problem addressed, the proposed mechanism or observed finding, its scope, and its implications for teacher preparation. These elements informed a functional classification of AI activities, a proposed learning sequence and an assessment matrix. Examples in the article are constructed instructional scenarios rather than records of classroom implementation or transcripts from an AI system.

The framework focuses principally on teacher-education seminars in which an instructor can supervise the selection and review of AI contributions. It does not assume direct use of public AI services by schoolchildren. Subsequent school-based application would require separate consideration of age, access, institutional procedures and the characteristics of the particular service. No participant data, original experiment, estimated effect size or validated competence scale is reported.

Analysis and results

Selecting an instructional function before selecting a tool

The first analytical result is a functional distinction among AI activities. Generating a draft, simulating an interaction and offering an evaluation create different learning opportunities and different verification demands. Grouping them under a general instruction to "use AI" leaves the educational purpose unclear. Table 1 identifies the decisions that should remain with the prospective teacher.

Table 1 AI functions and the decisions retained by the student teacher

Function	Possible contribution	Required professional judgement
Drafting resources	An example, explanation or task variant	Check content, objective and learner suitability

Function	Possible contribution	Required professional judgement
Formative feedback	A critique against stated criteria	Verify the comment and select a useful next step
Practice simulation	A constructed dialogue or pupil response	Recognise simulation limits and test teaching questions
Adaptation	An alternative format or level of explanation	Preserve the objective and check accessibility
Evaluation support	A tentative interpretation of work	Retain responsibility for evidence and final judgement

Source: Author's analytical classification. These are possible educational functions, not claims about the accuracy or capability of every available system.

The boundary between assistance and delegation is particularly important in evaluation. A student teacher may examine automated feedback as one interpretation of a response, but a model-generated grade should not be treated as an authoritative judgement simply because it is accompanied by a convincing explanation. The evaluator needs the learning objective, a defensible criterion and sufficient evidence about the learner's work. Where these are missing, automation can conceal uncertainty rather than resolve it.

Simulation also requires a clear boundary. An AI system instructed to act as a pupil can generate responses that are useful for rehearsing questions, but those responses do not represent an actual learner or establish how a class will behave. Student teachers should treat a simulated interaction as a constructed practice situation. Its value lies in the decisions it prompts them to examine, not in its presumed psychological authenticity.

The recommended selection question is therefore concrete: what part of this learning activity is improved by an AI contribution, and what evidence will show that improvement? If the answer concerns only faster production, the activity may still be useful for efficiency, but it should not automatically be presented as developing pedagogical competence. Learning and workload are related outcomes that require separate measures.

A sequence that keeps the student's reasoning visible

The proposed instructional sequence begins with an independent attempt. Before receiving automated suggestions, the student states an objective, identifies an anticipated difficulty and drafts a small teaching response. This creates a basis for later comparison. It need not be a lengthy complete lesson; its purpose is to make the student's starting interpretation visible and preserve an opportunity for initial reasoning.

The second phase assigns a bounded role to AI. The contribution might be an alternative explanation, a critique against a stated criterion or a possible counterexample. The task specifies what the system is being asked to contribute and what it should not replace. Such instructions organise the activity but do not guarantee system compliance. The instructor and student still need to inspect the response.

Verification is the third phase. Subject claims are checked against appropriate sources or worked reasoning. References are opened and examined rather than accepted because they look plausible. Recommendations are tested for fit with the intended learner and the assessment objective. A

verified fact can still be an unsuitable instructional choice, so factual checking and pedagogical checking remain distinct.

In the fourth phase, the student revises the material and records the reason for significant changes. Rejection of a suggestion is acceptable where justified. The revised product is then used in a short demonstration or discussed with peers. Finally, a new task is completed without AI so that the instructor can examine whether the relevant reasoning has transferred beyond the supported example.

Table 2 Proposed learning sequence

Phase	Student activity	Evidence retained
Independent attempt	Define the objective and draft a response	Initial reasoning and small teaching product
Bounded assistance	Request a specified contribution	Relevant prompt and selected response
Verification	Check subject claims and pedagogical fit	Annotated checks and supporting sources
Revision	Accept, reject or adapt suggestions	Revised product with reasons
Unaided transfer	Address a comparable new situation	Independent reasoning and performance

Source: Author's proposed instructional sequence. Duration and task complexity should be adjusted to the course; no effectiveness estimate is assigned to the sequence.

This sequence deliberately avoids defining success as maximal AI use. A student may conclude that the contribution is unnecessary or unsuitable. If that conclusion follows from a careful comparison, it can demonstrate competence. The educational objective is a defensible choice, not compliance with a requirement to use a particular technology in every activity.

Constructed scenario for mathematical explanation

A seminar can ask students to respond to the incorrect statement that one third plus one fourth equals two sevenths. This is a deliberately constructed misconception, not an observed pupil response. The student teacher first explains the conceptual difficulty and proposes a representation using equal-sized wholes. The task then introduces an AI-generated alternative explanation or an instructor-prepared example of the kind of response a system might produce.

Students examine whether the explanation preserves the meaning of the fractions, distinguishes the whole from its parts and shows why equal denominators are needed for this addition. They also consider what the learner is being asked to do. A correct worked answer can be insufficient if the pupil is expected to explain the reasoning but is given no opportunity to reconstruct it. Conversely, an attractive diagram may be misleading if the wholes have different sizes.

The required product includes an annotated explanation, a revised teaching response and a brief account of what was accepted or rejected. An unaided follow-up might use a different pair of fractions and require the student to identify a new representation problem. Assessment then addresses conceptual judgement across situations, not merely the successful correction of the example already discussed.

No automated response is assumed to be wrong in advance. The activity must allow students to recognise an accurate and useful suggestion as well as a problematic one. Otherwise, the task teaches a fixed attitude towards AI rather than the capacity to evaluate it. The same review procedure should be applied to instructor-created materials so that verification becomes a general professional habit.

Constructed scenario for differentiated feedback

A second seminar task can use a short anonymised or deliberately constructed piece of pupil writing. The prospective teacher identifies one learning priority and drafts feedback before consulting AI. The system is then asked to propose an alternative comment for the same objective. Students compare the comments for specificity, accuracy, tone and the action they invite the learner to take.

The exercise distinguishes feedback that corrects the product from feedback that helps the learner revise it. An automated rewrite may create a stronger paragraph while leaving the pupil uncertain about what changed. A more useful comment might identify the unsupported claim and ask for a relevant example, but its suitability depends on the learner's understanding and the task. The student teacher must make that judgement explicit rather than accept a general promise of personalisation.

Differentiation should also be separated from simplification. Reducing vocabulary can help access in some situations, yet removing the central reasoning demand changes the objective. Students can be asked to produce an accessible version that preserves the intended cognitive work, then explain the adjustment. CAST's guidance on offering different means of participation and expression provides a relevant design perspective [7], without implying that an AI-generated adaptation is automatically inclusive.

The final submission records the original feedback, the selected automated contribution and the student's revised comment. A short oral explanation can clarify why one feature was retained and another removed. The instructor evaluates the quality of the decision and whether the resulting feedback is usable, rather than the quantity of generated alternatives.

Assessing products and professional autonomy separately

Assessment needs two connected layers. The first addresses the teaching product: conceptual accuracy, alignment with the objective, accessibility and practical usability. The second addresses the learner's professional reasoning: identification of weaknesses, source verification, justification of revisions and transfer to a new task. These layers should be reported separately before considering any overall judgement.

Table 3 Assessment of products and professional reasoning

Layer	Criterion	Observable evidence
Teaching product	Conceptual accuracy	Correct explanations and representations
Teaching product	Instructional alignment	Task and assessment match the objective
Teaching product	Accessibility and usability	Suitable format and clear learning action

Layer	Criterion	Observable evidence
Professional reasoning	Verification	Claims checked against appropriate evidence
Professional reasoning	Justified adaptation	Reasons for accepting or rejecting suggestions
Professional reasoning	Independent transfer	A defensible decision on a new unaided task

Source: Author's proposed assessment matrix. It is a formative design tool, not a validated psychometric scale or an automated grading protocol.

A portfolio can contain a small number of selected decision records rather than an exhaustive conversation history. Students explain their starting point, the relevant contribution, their verification and the change made. Keeping only educationally necessary material reduces reporting burden and avoids collecting unrelated personal information. Where interaction records are required, the task should specify their purpose and who can access them.

Independent transfer tasks should change the content while retaining a comparable pedagogical demand. Repeating the same exercise may primarily measure familiarity. Similarly, an oral defence alone can favour verbal fluency unless criteria focus on the underlying reasoning and allow suitable alternatives. Assessment design should make it possible for students to demonstrate understanding without unnecessary barriers.

The rubric requires calibration. Instructors can assess selected examples independently, compare disagreements and refine descriptors that are interpreted inconsistently. This process does not establish full validity, but it is a useful initial quality check. Any claim that the framework measures professional competence reliably would require further empirical work across tasks, assessors and student groups.

Responsibility, access and implementation conditions

A course needs an explicit account of permitted assistance. Students should know when AI may be used, which decisions remain their responsibility and how assistance should be acknowledged. The purpose is to make learning evidence interpretable. An undisclosed generated explanation prevents the instructor from knowing which reasoning the student actually performed, while a clear account of assistance allows more accurate feedback.

Access conditions also affect interpretation. Students may have different devices, connectivity or access to paid features. Where a specific AI interaction is not itself the learning objective, an instructor-provided output or a shared supervised session can offer a comparable task. This does not eliminate all differences, but it avoids treating purchasing capacity as evidence of professional competence.

Privacy and ethics belong within the design rather than as a final administrative note. Real pupil work should not be entered into an external service without an appropriate basis and institutional permission. Constructed examples can often meet a seminar objective without using identifiable records. BERA's guidance supports treating ethical reflection as a continuing responsibility throughout educational inquiry [8]; it is used here as a professional reference rather than a substitute for applicable local requirements.

An institution should also consider verification time. Drafting may become faster while checking, correcting and adapting material takes longer. A credible workload evaluation would include both

stages. It should examine whether time is released for interaction and reflective practice, rather than counting only the seconds required to obtain a response. Claims of efficiency remain incomplete where quality-control work is excluded.

Teacher educators need opportunities to develop the same evaluative practices expected of students. A short technical demonstration is unlikely to resolve questions about learning evidence, bias or assessment. Programme development can begin with shared examples of useful and unsuitable outputs, followed by agreement on a limited set of tasks. The initial aim should be a coherent instructional routine rather than rapid adoption across every course.

Synthesis of analytical results

The analysis produces three methodological outcomes. First, AI use is classified by instructional function, with responsibility specified for each. Second, a learning sequence is proposed that preserves an independent starting point, requires verification and examines later transfer. Third, assessment separates product quality from professional autonomy. These outcomes provide an implementable framework, but they are not evidence of measured effectiveness in a teacher-education cohort.

The central design principle is that assistance should expose a decision to examination. Where AI supplies alternatives that a student compares and tests, it may create material for learning. Where it silently completes the judgement that is meant to be learned, a strong-looking product can conceal a missed opportunity. Which process actually occurs must be investigated through student work and independent performance, not inferred from the presence of the technology.

Discussion

The framework positions AI within the preparation of a reflective professional rather than as a separate technical competence. It is consistent with the relationships among subject, pedagogy and technology described in TPACK [1] and with UNESCO's emphasis on human agency [3; 4]. Its additional contribution is the explicit connection between a supported activity and a later unaided decision. This connection makes a common claim—AI helps students learn—more open to examination.

Several limitations remain. The proposed sequence has not been tested in a particular institution. Different subjects may require different verification practices, and students' prior knowledge can influence whether they recognise a problematic explanation. The framework also focuses on supervised seminar use; it does not describe all adaptive tutoring or predictive applications of AI. Tool changes may alter available functions, so activities should be reviewed when their technological conditions change.

A subsequent study could compare supported instructional designs while ensuring comparable subject content, time and feedback opportunities. Outcomes should include product quality, a delayed unaided task, verification behaviour and workload. Initial differences and instructor effects would need consideration. Student perceptions would be useful for understanding the experience, but satisfaction should not serve as a substitute for evidence of learning.

Finally, successful seminar performance does not establish improved outcomes for school pupils. That relationship would require an additional study in actual teaching practice. A staged research programme would first test the clarity and feasibility of the activities, then examine prospective teachers' learning, and only subsequently investigate classroom implications. This avoids attributing effects to AI that have not been measured.

Conclusion

The theoretical and methodological basis for AI in teacher education lies in the relationship between assistance and developing professional judgement. Technology should be assigned a

specific instructional function, and students should remain able to explain, verify and adapt its contribution. The quality of the generated product is only one part of the educational outcome.

The article proposes combining an independent attempt, bounded assistance, verification, revision and unaided transfer. Teacher-education programmes can use this sequence to design small, assessable activities before expanding adoption. Clear assistance rules, accessible participation and manageable verification procedures are necessary implementation conditions. Empirical testing is required to determine whether the proposed approach strengthens independent competence and under which circumstances it does so.

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