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TEACHER–AI DIALOGIC COLLABORATION AS A PEDAGOGICAL PARADIGM: MECHANISMS FOR INTEGRATING GENERATIVE ARTIFICIAL INTELLIGENCE INTO ADAPTIVE INSTRUCTIONAL DESIGN

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Abstract

The rapid proliferation of generative artificial intelligence (AI) tools in education demands a principled theoretical framework for understanding how teachers can effectively collaborate with these systems. This paper introduces and empirically validates the concept of Teacher–AI Dialogic Collaboration (TADC) as a foundational pedagogical paradigm for integrating generative AI into adaptive instructional design. Drawing on a quasi-experimental study conducted at two universities in Uzbekistan ($n = 120$; EG = 60, CG = 60), the paper argues that the defining characteristic of productive teacher–AI interaction is not command-based tool use, but iterative, reflective dialogue in which the teacher critically evaluates, refines, and pedagogically contextualises AI-generated content. Four interdependent pedagogical mechanisms are identified: motivational-axiological, cognitive-constructive, activity-design, and reflective-personal. The TALIA software system (registration certificate DT 202606091, 09.05.2026), developed on Google Gemini API, operationalises these mechanisms through a four-function content-generation architecture. Experimental results demonstrate statistically significant and practically large gains across all four competence components ($p < .001$; Cohen's $d = 2.98–4.94$). The findings reframe AI not as a productivity shortcut but as an intelligent pedagogical partner, with implications for teacher training policy and AI literacy standards in Central Asia and beyond.

Keywords: Generative AI; pedagogical mechanisms; adaptive instructional design; Teacher–AI Dialogic Collaboration; TALIA; teacher training; prompt engineering; Uzbekistan.

Introduction

The emergence of large language models (LLMs) — ChatGPT, Google Gemini, Claude — has fundamentally altered the conditions under which teachers design instruction. Where lesson preparation once required 45–60 minutes of manual drafting, a competent user of generative AI can produce a differentiated lesson plan, a three-level worksheet, and a Bloom's-aligned assessment battery within eight to twelve minutes [11, 19]. This temporal compression is not merely a convenience; it represents a structural shift in the cognitive economy of teaching. Yet the pedagogical literature has been slow to theorise this shift. The dominant framing in educational technology — that AI is a 'tool' to be 'used' — is insufficient. Tools are passive; they do not generate novel content, refine outputs in response to feedback, or adapt their register to a specific classroom context. Generative AI does all three, provided the teacher engages it in sustained, reflective dialogue. This paper argues that the conceptual move from 'AI as tool' to 'AI as dialogic partner' has direct consequences for how teacher training programmes are designed, what competences they prioritise, and how pedagogical quality is assessed.

Three prior articles from the same research programme have addressed complementary dimensions of this problem: the four-component competence structure and its diagnostic instruments, the six-block pedagogical model, and the technical architecture of the TALIA content-generation system. The present paper focuses on the concept of 'pedagogical mechanism' itself — what it means, why the standard definition is inadequate for an AI-mediated context, and how the TADC paradigm reframes the relationship between teacher, AI, and adaptive learning design [20].

Literature Review

The Concept of 'Pedagogical Mechanism' in General Pedagogy

The term 'pedagogical mechanism' has been used in the tradition of general pedagogy (13.00.01) to denote the internal workings of a pedagogical

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phenomenon — the specific conditions, operations, and processes that cause a desired educational outcome to occur [15, 22]. The concept is distinct from 'method' (a technique applied by the teacher) and 'technology' (a reproducible sequence of operations). A mechanism, by contrast, is a theoretical construct that explains why a particular pedagogical configuration produces its effects [9].

Standard definitions of pedagogical mechanism, however, were formulated before the advent of generative AI. They assume a dyadic teacher–learner interaction, occasionally mediated by digital tools, and do not account for a triadic configuration in which an AI system participates actively in content generation, feedback provision, and adaptive sequencing. This theoretical gap creates a practical problem: without a mechanism-level account of teacher–AI interaction, institutions lack principled criteria for designing preparation programmes, assessing teacher competence, or evaluating the quality of AI-generated instructional materials.

Prior Research on AI in Teacher Preparation

Table 1 maps key prior studies on AI integration in teacher preparation and identifies the specific gap that the present research addresses.

Table 1. Mapping of prior research on AI integration in teacher preparation

Researcher (Year)	Focus	AI Generation	Gap Identified
Shirokih (2007) [22]*	CS teachers + expert systems	1st gen (Prolog)	No generative AI; only CS teachers
Isaeva (2013) [8]	Vocational teachers + AI elements	2nd gen (ITS)	Vocational only; no adaptive design
Rozov (2024) [14]	CS teachers + modern AI	3rd gen (ML)	CS subject only; no all-teacher scope
Salakhova (2022) [22]*	School students learning AI	General AI literacy	Students, not teachers; no design focus
Xasanov (2026) [20]	**All teachers + generative AI design**	**4th gen (GenAI)**	**Present study — fills the gap**

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* Reference numbers for Shirokih and Salakhova are consolidated under [22] (Zagvyazinsky) pending full database retrieval; primary citations are in the dissertation [20].

The table reveals an 18-year trajectory in which each successive generation of AI technology created a corresponding generation of research, yet none addressed the integration of generative AI tools into the instructional design practices of all-subject teachers within general pedagogy theory [8, 14]. The critical gap is not technological but theoretical: the field lacks a mechanism-level account of how productive teacher–AI collaboration functions.

The Dialogic Tradition as Theoretical Resource

The most productive theoretical resource for filling this gap is the dialogic tradition in educational philosophy. Bakhtin's concept of dialogism — the idea that meaning is always co-constructed in the encounter between voices — has been extensively applied to classroom discourse [3]. Vygotsky's zone of proximal development similarly foregrounds the constitutive role of mediated interaction in cognitive development [18]. More recently, Mercer demonstrated how exploratory talk creates conditions for collaborative knowledge construction [10], and Alexander showed how dialogic teaching transforms the cognitive quality of classroom interaction [2].

Recent scholarship has begun to apply dialogic frameworks to human–AI interaction in educational settings [1, 4, 7]. These studies consistently find that the quality of AI-generated educational content is not a function of the AI system's capabilities alone, but of the quality of the dialogue that the human interlocutor initiates and sustains. A teacher who issues a single, vague command receives generically adequate but pedagogically thin output. A teacher who engages in iterative, context-rich, critically evaluative dialogue receives output that is meaningfully differentiated, Bloom-aligned, and contextually appropriate.

The Teacher–AI Dialogic Collaboration (TADC) Paradigm

Redefining the Pedagogical Mechanism for an AI-Mediated Context

The present study proposes the following definition, extending the classical concept to account for triadic (teacher–AI–learner) pedagogical configurations:

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A pedagogical mechanism, in the context of generative AI-mediated instruction, is a coherent didactic configuration that (a) operates through sustained, iterative, reflective dialogue between the teacher and the AI system; (b) is governed by explicit pedagogical principles (purposefulness, dialogism, differentiation, reflexivity, ethical responsibility); (c) maps onto specific competence components; and (d) produces measurable, transferable improvements in the quality of adaptive instructional design.

This definition carries four operational implications. First, the teacher's role shifts from executor to evaluator: the AI generates a draft; the teacher critically assesses, refines, and contextualises it. Second, the quality of output depends on the quality of the prompt — hence prompt engineering is not a technical skill but a pedagogical one [19]. Third, the interaction is inherently iterative: a single exchange does not constitute dialogue; productive teacher–AI collaboration unfolds across multiple cycles of generation, evaluation, revision, and re-generation. Fourth, the interaction must be reflexive: teachers who do not consciously reflect on their AI-collaboration practice do not develop transferable competence [4, 13].

Four Pedagogical Mechanisms and Their Architecture

The TADC paradigm comprises four interdependent mechanisms. Each mechanism is characterised by a specific function, a set of pedagogical conditions, and a corresponding component of the AI-oriented adaptive design competence (AOADC). Table 2 presents the architecture.

Table 2. The four TADC mechanisms: competence components, TALIA functions, and key pedagogical conditions

Mechanism	Competence Component	TALIA Function	Key Pedagogical Condition
Motivational-Axiological	Motivational-value	Demo & WOW-effect module	Teacher perceives AI as professional value
Cognitive-Constructive	Cognitive	Prompt-engineering training	Iterative dialogue with generative AI
Activity-Design	Organisational-activity	4-function content generator	Practical creation of adaptive lesson plans
Reflective-Personal	Personal (reflective)	Weekly journal + portfolio	Critical evaluation of AI-generated output

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The motivational-axiological mechanism addresses a consistent finding in teacher AI-adoption research: negative affective orientation blocks skill acquisition even when technical knowledge is present [1]. The 'WOW effect' — teachers observing in real time that AI reduces lesson preparation time by 80–90% while maintaining quality — was deliberately designed into the first session of the experimental course as a mechanism for restructuring the teacher's professional self-concept [16].

The cognitive-constructive mechanism targets the knowledge base required for pedagogically responsible AI use: understanding of LLM functioning, mastery of prompt-engineering principles, knowledge of Bloom's taxonomy as an organising framework for AI-generated tasks, and awareness of ethical constraints including academic integrity, hallucination detection, and data privacy [5, 9].

The activity-design mechanism is the operational core of the paradigm. It involves the creation of actual instructional artefacts — SMART-objective lesson plans, three-level (A/B/C) differentiated worksheets, Bloom-aligned assessment batteries, multimedia resource packages — through sustained dialogic interaction with the AI system. The TALIA platform's four-function architecture directly operationalises this mechanism [20].

The reflective-personal mechanism ensures that competence generalises beyond the training context. Weekly reflective journals, structured peer discussion, and a professional portfolio collectively create conditions for teachers to develop meta-cognitive awareness of their AI-collaboration practice. Without this mechanism, even technically proficient AI users remain dependent on specific prompts and platforms [4, 6].

Seven Governing Principles of the TADC Paradigm

The TADC paradigm is governed by seven principles that differentiate dialogic AI collaboration from instrumental AI use:

– Purposefulness: every teacher–AI exchange is framed by an explicit pedagogical goal.

– Systematicity: the four mechanisms are implemented in sequence and interdependently.

– Dialogism: interaction with AI is iterative, critical, and responsive — not one-shot [3, 10].
– Differentiation: AI-generated content is always evaluated and adapted to specific learner profiles.
– Reflexivity: teachers maintain ongoing meta-cognitive awareness of their AI-collaboration practice [13].
– Openness: the paradigm accommodates new AI systems as the technological landscape evolves.
– Ethical responsibility: academic integrity, attribution, and critical evaluation of AI outputs are non-negotiable [5, 17].

Methods

Research Design and Participants

A quasi-experimental pre-test/post-test control group design was employed across the 2024–2025 academic year at two institutions: Jizzax State Pedagogical University (primary site) and Samarkand State University. One hundred and twenty fourth-year pre-service teachers enrolled in pedagogy programmes participated (EG = 60, CG = 60). Pre-test equivalence was confirmed for age ($M = 21.4$, $SD = 0.6$), gender composition, GPA, and prior AI tool experience (all $p > .05$, Student's t-test for independent samples). Baseline data confirmed low AOADC levels in both groups: motivational $M = 2.85/5.0$; cognitive $M = 37.6/100$; activity-design $M = 7.9/20$; reflective $M = 6.3/16$.

Intervention

The EG participated in a 14-week course ('Designing Adaptive Learning Processes with AI') delivered through the TALIA platform (registration certificate DT 202606091, 09.05.2026). Four sequenced modules were aligned with the TADC mechanisms: (1) Foundations and AI Orientation (Weeks 1–3); (2) Prompt Engineering and Cognitive Frameworks (Weeks 4–7); (3) Adaptive Content Design Workshop (Weeks 8–11); (4) Reflection, Portfolio, and Transfer (Weeks 12–14). Each 90-minute session combined brief theoretical input with extended hands-on AI-mediated instructional design practice, followed by structured peer discussion and reflective journalling. The CG studied the standard 'Digital

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Pedagogy' module without access to AI content-generation tools or the TADC framework.

Instruments and Data Analysis

Four purpose-built instruments were administered at pre-test, mid-point (Week 7), and post-test:
– MSA-2024 (Motivational Survey of AI Attitudes): 20-item Likert scale (1–5); Cronbach's α = .84.
– KBT-2024 (Knowledge Base Test): 25-item cognitive test covering theoretical knowledge, prompt engineering, and Bloom application; KR-20 = .81.
– AKR-2024 (Activity-Design Rubric): expert evaluation of AI-generated lesson materials on 5 criteria; Cohen's κ = .79.
– RJS-2024 (Reflective Journal Scale): weekly assessment on 4 criteria; maximum 16 points.
Between-group comparisons used Student's t-test for independent samples. Effect sizes were calculated using Cohen's d. Level distributions were analysed with Pearson's chi-square. Statistical significance was set at α = .05.

Results

Table 3 presents the pre-test and post-test means for both groups, together with inferential statistics.

Table 3. Pre-test and post-test results by competence component: EG vs. CG (n = 120)

Component (Scale)	EG Pre (M)	EG Post (M)	CG Post (M)	p	Cohen's d
Motivational (1–5)	2.84	4.31	2.87	<.001	2.98
Cognitive (0–100)	37.6	74.6	42.5	<.001	3.74
Activity-Design (5–20)	7.9	16.8	8.3	<.001	4.07
Reflective (4–16)	6.3	12.4	6.7	<.001	3.12
Composite (0–100)	**38.4**	**79.2**	**41.1**	**<.001**	**4.94**

All four competence components showed statistically significant between-group differences at post-test (p < .001), with Cohen's d values ranging from 2.98

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(motivational) to 4.94 (composite). By conventional benchmarks, all effects are very large ($d > 2.0$). The composite score increased from a pre-test baseline of 38.4 in the EG to 79.2 at post-test, against a CG post-test mean of 41.1 ($d = 4.94$). Level distribution analysis confirmed the pattern: in the EG at post-test, 53.3% of participants reached the 'high' (creative-design) level versus 3.3% in the CG; chi-square confirmed highly significant distributional differences across all four components ($\chi^2 = 61.4$; $df = 2$; $p < .001$).

Mid-point data (T2, Week 7) allow mechanism-level interpretation. After the motivational-axiological and cognitive-constructive modules, the EG showed gains of +27% (motivational), +61% (cognitive), +69% (activity-design), and +14% (reflective). The modest mid-point reflective gain, followed by strong growth in the second half, confirms the delayed but robust effect of the reflective-personal mechanism — consistent with the theoretical prediction that reflective competence develops more slowly than instrumental skills [4]. The activity-design component showed the highest overall growth (+115% across the full course), confirming that hands-on, AI-mediated instructional design sessions were the primary driver of competence development.

Discussion

The effect sizes obtained substantially exceed those reported in prior comparable research. Isaeva (2013) confirmed statistical significance at $\alpha = .05$ but did not report effect size [8]; Rozov (2024) reports $d \approx 1.8$ for a CS-specific teacher preparation methodology [14]. The present study's d values of 2.98–4.94 are consistent with the expectation that generative AI, by providing immediate, personalised, and contextually rich feedback, amplifies the motivational and activity-design mechanisms beyond what earlier-generation AI tools could achieve [11, 21].

The 'WOW effect' warrants particular attention. Qualitative data from reflective journals ($n = 60$) consistently identified the first-session demonstration — participants generating a complete, differentiated lesson plan in 8–12 minutes versus the 45–60 minutes they typically spent — as the pivotal affective event. This observation aligns with Slastenin and Podymova's theoretical claim that the motivational component is the 'moving force' of pedagogical development [16],

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and with Adamakis and Rachiotis (2025), who demonstrate that affective orientation toward AI is a stronger predictor of effective AI use than technical knowledge alone [1].

The principle of dialogism was operationally visible in the iterative prompt-refinement sequences that participants developed over Weeks 4–7: from single-sentence commands to multi-turn exchanges specifying audience, Bloom level, differentiation tier, and subject-specific context [3, 18]. The principle of reflexivity was evident in the progressive deepening of reflective journal entries from descriptive accounts of AI-use episodes (Weeks 1–4) to critical analysis of the pedagogical decisions embedded in prompt design (Weeks 8–14) [13].

These findings also align with Darling-Hammond et al. (2020), who argue that deep learning requires active, socially situated, and emotionally engaging experiences [6]. The TADC paradigm operationalises all three conditions: activity (hands-on AI-mediated design), social situation (peer discussion and reflective dialogue), and emotional engagement (motivational-axiological mechanism). Cotton et al. (2023) further underline the importance of academic integrity protocols in AI-enhanced learning environments [5] — a concern directly addressed by the ethical responsibility principle of the TADC paradigm and by module content in the experimental course.

Conclusion

This paper has advanced the Teacher–AI Dialogic Collaboration (TADC) paradigm as a principled framework for integrating generative AI into adaptive instructional design. The central theoretical contribution is a revised definition of 'pedagogical mechanism' that foregrounds iterativity, criticality, and reflexivity as the distinguishing features of productive teacher–AI dialogue — extending the classical concept from dyadic to triadic (teacher–AI–learner) configurations.

Empirically, the four mechanisms identified — motivational-axiological, cognitive-constructive, activity-design, and reflective-personal — are distinct, sequentially interdependent, and collectively sufficient to account for statistically significant and practically large gains in AI-oriented adaptive design competence ($p < .001$; $d = 2.98–4.94$, $n = 120$). The TALIA platform (DT 202606091) and

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four diagnostic instruments (MSA-2024, KBT-2024, AKR-2024, RJS-2024) operationalise these mechanisms and are available for institutional adoption.

For policymakers, the findings support development of national AI competence standards for teachers aligned with the four-component AOADC model and consistent with international frameworks including DigComp 2.2 and the UNESCO AI Competency Framework for Teachers (2024) [17]. Future research should address long-term stability of TADC-developed competence, cross-national replication, and adaptation of the framework for in-service professional development contexts.

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