Asia Pacific Science Press

Journal of Educational Theory and Practice
ISSN(O):3005-9313
ISSN(P):3005-9305
Vol. 3 No.4 (2026)

Developing Ketul's Penta-Polar Teaching-Learning Model (KPTLM): Integrating Artificial Intelligence Beyond Previous Poles

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Abstract: Teaching-learning has historically been theorised through bipolar, tripolar and quadripolar schemes, yet the rapid entry of artificial intelligence (AI) into classrooms and extension services has outpaced these frameworks. A conceptual study was conducted during 2025 and 2026 to develop and position Ketul's Penta-Polar Teaching-Learning Model (KPTLM). An integrative theory-synthesis design was used. Nine historical and contemporary frameworks were purposively selected and compared on their components, status of technology and theoretical purpose; historical attributions were checked against primary sources, and pairwise relations were derived combinatorially. The comparison showed that existing frameworks specified two to four components and placed technology within teacher knowledge, the milieu or a mediating category. The resulting model placed an effective teaching-learning process at the centre of five interactive, non-hierarchical poles: teacher, learner, curriculum/content, learning environment and AI. Ten reciprocals pairwise relations and eight testable propositions were specified, and the model was applied to an AI-supported course in agricultural higher education. The study concluded that the model provides a coherent diagnostic and research framework for AI-integrated teaching-learning in teacher education, agricultural higher education and extension, subject to empirical validation.

Keywords: Pedagogical Framework; AI; Teacher Education; Learning Environment; Curriculum; Educational Technology; KPTLM

Published: Nov 12, 2026

DOI: https://doi.org/10.62177/jetp.v3i4.1812

1. Introduction

1.1 Research Background and Importance

Teaching-learning is commonly described as a transaction between a teacher and a learner, yet educational theory has long treated this pairing as an abstraction from a wider system. [1] described the educative process as bipolar involving an Educator pole and an Educand pole. [2] linked the child to the organisation of subject matter and social life of the community, which later textbooks label as being of a tripolar nature. [3] has stated that curriculum deliberation should consider four commonplaces, which are: teacher, learner, subject matter and milieu, and [4] has categorized educational theories based on four poles. Every scheme addresses the questions of its time and is relevant to them.

These schemes are now under pressure from two developments. First, there is an increasing production of instruction content, feedback and assessment by AI, not just transmission of it [5] [6] [7]. Second, learner-centred and competency-oriented reforms,

including India's National Education Policy 2020, travel across institutional and sociocultural settings whose conditions shape outcomes [8] [9].

Contemporary frameworks address parts of this change. Pedagogical content knowledge links the teacher and content [10]; technological pedagogical content knowledge (TPACK) adds technology as a domain of teacher knowledge [11], later extended with contextual knowledge [12] and with knowledge for the ethical use of AI-based tools [13]. Reviews nevertheless report that research on AI in education remains weakly connected to pedagogical theory and to educators [14] [15] [16]. No framework among those examined specifies the teacher, learner, curriculum, learning environment and AI simultaneously, non-hierarchically and relationally, with the teaching-learning process itself as the unit of analysis.

The present study proceeds from the working hypothesis that the quality of teaching-learning depends on the configuration of five interacting poles, and that AI functions as a distinct pole capable of reconfiguring relations among the other four rather than as a component of teacher knowledge or of the setting. Its objectives are to trace pole-based conceptualisations of teaching-learning, to identify what they leave under-specified, and to develop and position Ketul's Penta-Polar Teaching-Learning Model (KPTLM) with testable propositions. A conceptual theory-synthesis approach is used, since the problem is about the adequacy of the existing constructs, and their relation, a question that logically foreshadows measurement [17].

2. Methodology

The study was a conceptual, theory-development investigation carried out during 2025 and 2026 in the Department of Liberal Arts and Social Sciences, Manipal University Jaipur, Rajasthan. It followed the theory-synthesis design for conceptual articles described by [17] and the procedure for building conceptual frameworks described by [18], which involves mapping sources, identifying and categorising concepts, integrating them and validating the resulting framework against the literature. No human subjects were used and there was no primary data collected.

The source materials were obtained from the author's previous presentation of the teaching model, handbooks of historical teaching-learning schemes and literature and research on pedagogy, technology integration and AI in education, most of which was peer-reviewed, and recent studies in the field of extension education. The selection of sources was done purposefully and not systemically. A total of nine frameworks published from 1912 to 2023 were identified for comparison according to the following criterion: A framework was retained when at least two components of teaching-learning were named or when there was a place for technology or AI in teaching-learning.

Each retained framework was coded on four attributes: core components, number of components, status assigned to technology and theoretical purpose. Historical attributions of the bipolar, tripolar and quadripolar labels were checked against primary texts where these were accessible, and a label was treated as unverified when it was found only in secondary sources. Pole construction was based on components that occurred in each framework. The Relational Structure was computed Combinatorially, with the number of pairwise Relations acquired as

$$R = n(n - 1)/2$$

with n the number of poles and R the number of reciprocals pairwise relations. In this model there are 5 poles to centre relations and 10 (n = 5) reciprocal links. For each pairwise relation an illustrative mechanism was attributed, based on published literature. The framework for the propositions was constructed by posing the question: What would be the observable pattern if there was a mechanism, and indicators and appropriate empirical methods were attached to each proposition. Journal sources were verified using the Crossref, OpenAlex and GoogleScholar bibliographic information. Since it was a purposive selection, the gap claims were conditional on the compared set.

3. Results and Discussion

3.1 Evolution of Pole-Based Conceptualisations and the Remaining Gap

The comparison showed a gradual increase in the number of components specified by pole-based schemes, from two in [1] to four in [3] and [4] (Table 1). The bipolar attribution to Adams and the quadripolar attribution to Bertrand were supported by explicit polar language in the sources. The tripolar label applied to Dewey was not found in the primary writings consulted and was therefore treated as a secondary characterisation of a structure, relating to child, curriculum and society, that

Dewey's account does support. [19] conversational framework contained four components but was quadripolar only in an interpretive sense. Technology entered the tradition late and, where present, was located inside another category: the milieu [3], pedagogical interactions [4], the teacher-constructed environment [19] or a domain of teacher knowledge [11] [13].

Table 1: Comparison of pole-based and technology frameworks with KPTLM

Framework (source)	Core components	Status of technology	Relation to KPTLM
Bipolar process [1]	Educator pole; educand pole	Absent	Teacher–Learner, one of ten relations
Tripolar process* [2]	Child; curriculum; society	Absent	Anticipates three poles
Commonplaces [3]	Teacher; learner; subject matter; milieu	Part of milieu	Closest antecedent: four of five poles
Pedagogical content knowledge [10]	Teachers' content and pedagogical knowledge	Absent	Specifies the Teacher–Content relation
Quadripolar scheme [4]	Subject; content; Society; pedagogical interactions	Inside interactions element	Classify theories, not teaching events
TPACK [11] [12]	Technological, pedagogical, content and contextual knowledge	Domain of teacher knowledge	Specifies Teacher pole; no learner component
Conversational framework [19]	Teacher and learner concepts; environment; actions	Teacher-constructed environment	Context not a component
Learner-centred pedagogy [8]	Active learner; contextualised practice	Not central	Informs Learner and Learning Environment poles
Intelligent-TPACK [13]	TPACK plus ethics of AI-based tools	AI as teacher knowledge	Informs the Teacher–AI relation
KPTLM (present study)	Teacher; learner; curriculum/content; learning environment; AI	AI as co-equal pole	Five poles; ten relations

TPACK, technological pedagogical content knowledge; AI, artificial intelligence; KPTLM, Ketul's Penta-Polar Teaching–Learning Model. *Label not found in Dewey's primary writings consulted; treated as a secondary characterisation.

These findings indicate that the components of KPTLM are not individually new. Schwab's commonplaces already cover four of the five poles, TPACK now incorporates context [20], and Bertrand's interactions element includes communication technologies. The contribution claimed is therefore narrower than novelty of components. Three gaps exist in the set of comparisons: no framework explicitly mentions all five components together, and not in a hierarchical way; no framework mentions and theorises the relation of AI to all of five other components; no framework enumerates and theorises each relation between two components. The second gap is significant, as the recent research on AI in higher education still found that pedagogical support is limited and teachers' engagement is lacking [7] [14] and the adoption of AI in agricultural education is already high among agricultural students and professionals in India [21] [22]. While a teacher-knowledge framing provides insight into teacher knowledge needs, it does not provide insight into the changes that AI brings to the relationship between the learner and either the content or the environment without the teacher.

The historical process has its methodological implications. Each extension of the pole set introduced a new element that had been previously considered a 'background' - society in Dewey's account, the milieu in Schwab's and pedagogical interactions in Bertrand's. This is the same logic behind the present synthesis, where AI is not used in the background or as teacher knowledge but explicit. The verification exercise also reveals that labels that are repeated in teacher-education study material, such as the tripolar description of Dewey, are secondary interpretation. Attribution is important for a discipline that trains teachers and extension educators in these schemes, and to protect a new model from inheriting unsupported claims.

3.2 Architecture of Ketul's Penta-Polar Teaching-Learning Model

The synthesis resulted in a model in which the effective teaching-learning process was located at the center, and five poles, which are non-hierarchical and interactive, were obtained: Teacher, Learner, Curriculum/Content, Learning Environment

and Artificial Intelligence (Figure 1). The Teacher pole facilitates, designs, mentors and assesses; the Learner pole engages and constructs understanding from prior knowledge, motivation and identity; the Curriculum/Content pole supplies knowledge, skills, competencies and values embedded in them; the Learning Environment pole can be physical, institutional, sociocultural and policy conditions (not all of which are AI), such as learning management systems; and the AI pole can be a system that adapts, builds, or evaluates, from intelligent tutoring to generative AI. The poles were specified as analytically distinct but empirically entangled, reciprocal in influence and without fixed rank, although their salience may shift across tasks and phases. Each of the ten pairwise relations were linked to at least one documented mechanism (Table 2).

Four boundary conditions were attached to the architecture. The model applies to intentionally designed teaching-learning in formal settings, such as schools and universities, and in non-formal settings, such as extension training and farmer field programmes; it is not proposed as an account of incidental learning. Non-AI tools, from chalkboards to learning management systems, belong to the Learning Environment pole, so the model remains usable where AI is absent and the AI pole is simply weak. Pedagogical and ethical responsibility is assumed to remain with human educators and institutions, consistent with policy guidance on AI in education [23]. Finally, the five poles are distinguished analytically, and their interrelations rather than their separate strengths are treated as the main determinant of the teaching-learning process.

Figure 1; Ketul's Penta-Polar Teaching-Learning Model (KPTLM)

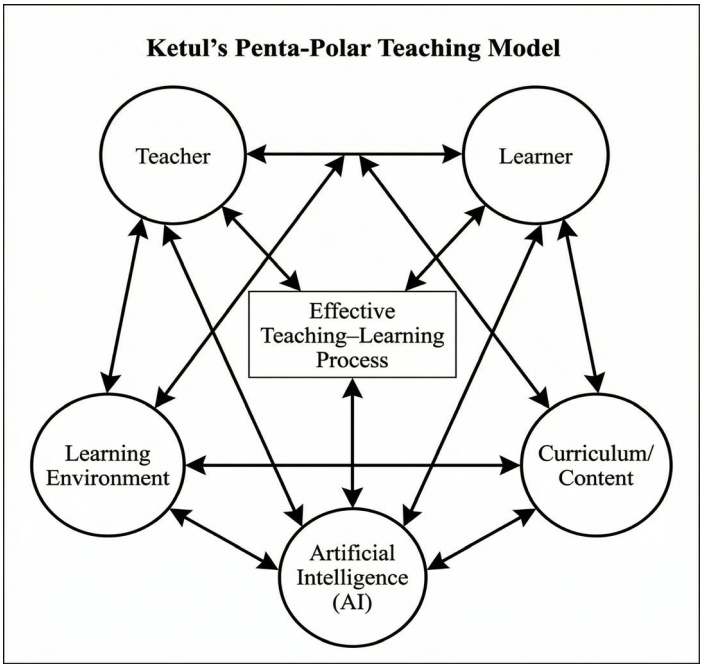


Table 2; Illustrative mechanisms shown via the ten pairwise relations of KPTLM

Relation	Illustrative mechanism	Literature anchor
Teacher-Learner	Scaffolding and feedback adapted to understanding and autonomy	[19] [24]
Teacher-Content	Transformation of content into teachable representations and sequences	[10]
Teacher-LE	Adapting teaching to resources, culture and policy	[8]
Teacher-AI	Orchestrating AI tools; AI-related professional knowledge	[13] [22]
Learner-Content	Cognitive, behavioural and emotional engagement with tasks	[25]
Learner-LE	Access to devices, connectivity and modes of learning	[26]
Learner-AI	Dependence, integrity concerns and use	[6] [21]
Content-LE	Localising content to the setting	[11] [12] [20]
Content-AI	How content is represented, accessed and generated	[5]
LE-AI	Infrastructure, policy and norms for responsible AI use	[23] [27]

LE, learning environment; AI, artificial intelligence.

The architecture departs from earlier schemes in three respects. First, the centre is a process judged against educational purposes rather than an outcome assumed in advance; following [28], effectiveness is evaluated across qualification, socialisation and subjectification, not efficiency alone. Second, AI occupies its own pole because adaptive and generative systems, unlike earlier media, take part in producing content and feedback [5] [6]. Placing AI beside the teacher, rather than inside teacher knowledge, makes hybrid arrangements such as teacher-AI complementarity in classroom orchestration [29] visible as relations to be designed. Third, the Learning Environment pole carries context, which recent studies in agricultural education show to be decisive: availability of information and communication technology was the most influential criterion in students' e-learning preferences [26], and inadequate laboratories, limited software training and insufficient practical exposure were among the constraints prioritised in an assessment of teaching effectiveness [30]. The strongest counterargument is that AI is reducible to the learning environment or to content. The model's response is that AI acts on all four other poles, including the learner directly, and therefore warrants separate analysis; whether this separation adds explanatory value remains an empirical question.

3.3 Recommendations and Suggestions for Teachers and Extensionists

Eight propositions were derived from the mechanisms (Table 3). These included: configurational fit, conditioning of effects of AI by learning environment, reconfiguration of relationships by AI, reciprocal adaptation, threshold constraint, relevance mediation, agency preservation and salience shift. These were each matched with observable indicators and methods, but none of these have been tested.

Table 3: Proposal of KPTLM with indicators and methods of testing

Proposition	Observable indicators	Suitable methods
P1 Fit: learning is based on fit among all poles (not one strong pole)	Rated alignment of poles outcomes	Fuzzy-set comparative analysis
P2 Conditioning: AI effects vary with environment and teacher design	Between-site variation in tools effects	Multi-site quasi-experiments; multilevel moderation
P3 Reconfiguration: AI modifies communicative patterns, and not just efficiency	Who provides feedback, when and how	Discourse analysis; learning-analytics logs
P4 Reciprocity: closed learner-data feedback loops improve learning	Instructional adjustments after learner data	Design-based research; lesson video coding
P5 Threshold: a severe deficit in one pole caps learning	Limiting conditions despite strong poles	Necessary condition analysis; case studies
P6 Relevance: contextual relevance of content mediates engagement	Perceived relevance; engagement	Structural equation modelling; panel surveys
P7 Agency: AI benefits increase when users can ask questions and override the outputs.	Verification and override rates	Experiments; surveys; interviews
P8 Salience: The limiting pole, shifts during phases and time	Coded focus of teacher decisions	Video coding; stimulated recall

AI, artificial intelligence. All propositions are conceptual and untested.

There are three differences between architecture and the previous schemes. Firstly, the centre is considered a process and not an outcome predetermined for educational purposes in line with [28] the effectiveness is judged not only with reference to efficiency. Second, AI is in its own pole, adaptive and generative systems, unlike previous media, are involved in the making of content as well as feedback [5] [6]. The agency claim in P7 is consistent with the argument for human-AI hybrids where teachers and learners are still in charge of the outputs of the AI [6] [15]. The propositions thus do not challenge current knowledge but rather build upon it and contribute something new: they bring these effects together into one relational system

and thus enable them to be investigated.

The model is used in an undergraduate extension education course where the students use generative AI to produce farm advisories, leading them beyond the tool. The ones that the Teacher pole ought to shift are in providing content; the Learner pole that ought to rise in concern are over-reliance and academic integrity, some of which were reported by non-users of ChatGPT [21]; the Curriculum/Content pole ought to include output and evaluation that cannot be avoided by AI drafting; and the AI pole ought to involve accuracy, bias and data-governance issues [23]. P1 anticipates that the learning outcomes may be uneven if the learning AI tool is capable, but the learning outcomes are unclear, P2 suggests that there may be different learning outcomes in different institutions due to the differences in their infrastructure, and P7 suggests that there may be greater learning effects when students verify and override the results of the learning AI tool. Validated digital learning engagement instruments can be used to measure the engagement of learners in such settings [25].

The model provides a planning audit with five questions for teacher education and extension capacity building: what will the teacher do, what do the learners bring, what competencies are the subject of the learning, what environmental conditions facilitate or hinder the activity, and how is AI affecting the other relations, as well as a sixth question, what will be recognised as effective learning. It is not meant to supplant TPACK, which can designate the Teacher pole, or instructional design principles which are applied within the model. There are limitations to the study. The set of frameworks was selected purposefully, therefore the gaps claimed are dependent on the frame set; the model is not yet validated; the poles overlap at the extremes, and the assumption of non-hierarchy may mask the power dynamics between teachers and learners, institutions and technology providers. A staged validation agenda therefore follows: a registered scoping review to test the gap claims, a Delphi study of pole definitions and propositions, development of a rating instrument for pole alignment, design-based research in teacher-education and extension course [30], and multi-site tests using necessary condition analysis [31] and multilevel models. The model would be weakened if a separate AI pole added no explanatory value over four-pole alternatives.

Conclusion

Pole-based theories of teaching-learning have expanded from two to four components, but none of those examined treats artificial intelligence as a distinct component or specifies every relation among teacher, learner, curriculum, learning environment and intelligent technology. Ketul's Penta-Polar Teaching-Learning Model is filling this gap, focusing the effective teaching-learning process at the centre of five co-equal, interacting poles, and stipulating ten reciprocating relations and eight testable propositions. The rest of the poles are in a relation reconfigured by the working hypothesis that Artificial Intelligence doesn't only support it but is also a reconfiguration of it, which hasn't been empirically tested yet. The model also presents an opportunity for teacher educators, agricultural universities, and extension organisations to audit their way of designing courses and advisory programmes that can incorporate AI without supplanting human judgement and that do not overlook local conditions. Now it needs to be systematically validated at institutions and in learning contexts.

Funding

No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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