



Teachers' Attitude Towards Artificial Intelligence in Education: A Conceptual Framework for Understanding Technology Acceptance in the AI Era

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Abstract

The rapid diffusion of artificial intelligence (AI) technologies into classrooms, learning management systems, and administrative workflows has made teacher attitude a decisive variable in determining the pace and quality of educational transformation. While a growing body of empirical work reports on teachers' AI readiness across contexts, comparatively less attention has been paid to building an integrated conceptual apparatus that explains why such attitudes form, persist, or change. This paper undertakes a theoretical synthesis of attitude theory and technology-acceptance scholarship—drawing on the Theory of Reasoned Action, the Theory of Planned Behaviour, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Rogers' Diffusion of Innovations—to propose an integrated conceptual framework for understanding teachers' attitudes towards AI in education. The framework organises attitude along cognitive, affective, and conative dimensions, situates these within antecedent conditions of digital self-efficacy, institutional support, and perceived pedagogical value, and links them to behavioural intention and eventual classroom adoption. The paper argues that such a framework is a necessary theoretical precursor to sound psychometric scale construction, since item generation, domain specification, and construct validity all depend on a well-articulated model of the underlying attitude construct. Implications for teacher education, policy, and future scale-development research are discussed.

Keywords: *teacher attitude; artificial intelligence in education; technology acceptance; conceptual framework; scale construction*



1. Introduction

Artificial intelligence has moved from the periphery of educational discourse to its centre. Adaptive learning platforms, automated assessment engines, intelligent tutoring systems, and generative AI tools capable of producing lesson content, feedback, and explanations are now embedded in the everyday infrastructure of schooling. Governments and universities across India, including institutions operating under the National Education Policy (NEP) 2020, have signalled an explicit commitment to integrating AI literacy and AI-assisted pedagogy into teacher preparation programmes. Yet infrastructure and policy intention alone do not guarantee classroom-level adoption. Decades of research on educational technology diffusion converge on a single, recurring finding: the attitude of the teacher, more than the sophistication of the tool, is the proximate determinant of whether a technology is meaningfully integrated into practice or quietly abandoned after a pilot phase.

The urgency of understanding teacher attitude towards AI is compounded by the distinctive character of AI as a technology. Unlike earlier waves of educational technology—interactive whiteboards, learning management systems, or basic computer-assisted instruction—AI systems exhibit a degree of autonomy, opacity, and adaptivity that unsettles conventional assumptions about who or what performs the pedagogical act. Teachers are asked not merely to operate a tool but to negotiate a shifting division of cognitive and pedagogical labour with a system whose internal reasoning is frequently non-transparent. This raises attitude-relevant concerns that are qualitatively distinct from those associated with earlier technologies: concerns about de-skilling, professional identity, academic integrity, algorithmic bias, and the ethical status of automated decision-making in assessment and feedback.

Despite the proliferation of empirical studies measuring teachers' attitudes towards AI—frequently through researcher-constructed questionnaires of variable psychometric quality—there remains a shortage of theoretical work that explains the structure of the attitude construct itself before it is measured. This is a consequential gap. Scale construction, as an empirical exercise, is only as sound as the conceptual model that precedes it: domain specification, item generation, and content validity all depend on prior theoretical clarity about what 'attitude towards AI' comprises and how its components relate to one another and to behaviour. This paper addresses that gap. It offers a theoretical synthesis of established attitude and technology-



acceptance theories and proposes an integrated conceptual framework tailored to the specific case of teachers' attitudes towards artificial intelligence in education. The framework is intended to serve as the conceptual scaffolding for subsequent empirical and psychometric work, including scale construction and standardization efforts of the kind increasingly undertaken in Indian teacher-education research.

2. Conceptualising Attitude: A Tripartite View

Attitude has long been understood in social psychology as a relatively enduring evaluative orientation towards an object, comprising three interrelated components: a cognitive component (beliefs and knowledge about the object), an affective component (feelings and emotional responses towards the object), and a conative or behavioural component (the predisposition to act in particular ways towards the object). This tripartite model, associated with early attitude theorists and consolidated in subsequent social-psychological research, remains the dominant lens through which attitude constructs are operationalised in educational measurement.

Applied to AI in education, the cognitive component encompasses teachers' beliefs about what AI systems can and cannot do, their understanding of underlying mechanisms such as machine learning and natural language generation, and their appraisal of AI's instructional utility. The affective component captures the emotional valence teachers attach to AI—enthusiasm, curiosity, anxiety, scepticism, or threat—which research consistently shows to be only loosely coupled with cognitive appraisal; a teacher may hold accurate and even favourable beliefs about AI capability while nonetheless experiencing anxiety about its classroom implications. The conative component refers to teachers' behavioural predispositions: willingness to experiment with AI tools, intention to integrate them into lesson planning, or conversely, avoidance and resistance behaviours. A theoretically adequate attitude scale must sample items across all three dimensions rather than collapsing them into a single undifferentiated 'attitude' score, since doing so obscures diagnostically useful variation—for instance, a teacher population that is cognitively informed but affectively anxious requires a different intervention than one that is affectively enthusiastic but cognitively under-informed.



3. Theoretical Frameworks Informing Technology-Related Attitude

3.1 The Theory of Reasoned Action and the Theory of Planned Behaviour

The Theory of Reasoned Action posits that behaviour is preceded by behavioural intention, which is itself a function of attitude towards the behaviour and subjective norms—the perceived social pressure to perform or not perform the behaviour. The Theory of Planned Behaviour extended this model by introducing perceived behavioural control, acknowledging that intention alone is insufficient to predict behaviour when individuals lack the resources, skills, or opportunities to act. For teachers, perceived behavioural control with respect to AI integration is shaped by digital self-efficacy, access to institutional infrastructure, availability of training, and administrative support. A theoretical account of teacher attitude towards AI that omits perceived control risks over-predicting adoption among teachers who hold favourable attitudes but operate within resource-constrained institutional environments, a condition especially relevant to the heterogeneous infrastructural landscape of Indian higher secondary and teacher-education institutions.

3.2 The Technology Acceptance Model

The Technology Acceptance Model (TAM) proposes that technology adoption behaviour is primarily determined by two beliefs: perceived usefulness (the degree to which a person believes a technology will enhance their performance) and perceived ease of use (the degree to which a person believes using the technology will be free of effort). TAM has been extensively validated across educational technology contexts and offers a parsimonious account of the cognitive antecedents of attitude. Applied to AI, perceived usefulness maps onto teachers' judgements about whether AI tools genuinely improve instructional efficiency, differentiation, or assessment quality, while perceived ease of use maps onto judgements about the accessibility and usability of AI interfaces, particularly for teachers with limited prior exposure to advanced digital tools. TAM's central limitation for the present purpose is its narrow cognitive focus; it under-theorises the affective and ethical dimensions that are disproportionately salient in AI adoption, where concerns about academic integrity, bias, and professional displacement carry emotional and normative weight that a purely instrumental usefulness-ease framework does not capture.



3.3 The Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) synthesises TAM and several related models into four core determinants of behavioural intention and use: performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by variables such as experience, voluntariness of use, gender, and age. UTAUT's principal contribution to the present framework is its explicit inclusion of social influence and facilitating conditions as distinct constructs, which allows the conceptual model to accommodate the strongly collegial and institutionally mediated character of teacher decision-making. Teachers rarely adopt or reject AI tools in isolation; peer modelling, departmental norms, and leadership endorsement exert measurable influence on individual attitude formation and, subsequently, on adoption intention.

3.4 Rogers' Diffusion of Innovations

Rogers' Diffusion of Innovations theory contributes a temporal and population-level perspective absent from the individually focused models above. It characterises adopters along a continuum from innovators to laggards and identifies five perceived attributes of an innovation—relative advantage, compatibility, complexity, trialability, and observability—that predict its rate of adoption. Compatibility, in particular, is theoretically significant for AI in education: teachers' attitudes are shaped not only by AI's instrumental usefulness but by the degree to which AI-mediated pedagogy is perceived as compatible with existing professional values, curricular mandates, and conceptions of what constitutes legitimate teaching and assessment. Where AI is perceived as incompatible with prevailing pedagogical values—for instance, where automated feedback is seen as eroding the relational core of teaching—attitude is likely to remain negative regardless of demonstrated usefulness.

4. Towards an Integrated Conceptual Framework

Building on the theoretical strands reviewed above, this paper proposes an integrated conceptual framework organised around four layers: antecedent conditions, the tripartite attitude construct, behavioural intention, and adoption behaviour, with feedback loops connecting adoption experience back to antecedent conditions.



4.1 Antecedent Conditions

Antecedent conditions comprise the individual and contextual factors that shape the formation of attitude prior to its behavioural expression. At the individual level, these include digital self-efficacy (a teacher's belief in their own capacity to learn and operate AI tools), prior technology experience, subject-domain background, and epistemic beliefs about teaching and learning. At the institutional level, antecedent conditions include the availability of professional development, leadership endorsement, infrastructural access, and the presence or absence of institutional AI policy. At the socio-cultural level, they include prevailing normative discourse about AI in the media and professional community, and broader societal narratives—optimistic or dystopian—about automation and employment.

4.2 The Tripartite Attitude Core

The tripartite attitude construct described in Section 2 sits at the centre of the framework, with the cognitive, affective, and conative components treated as correlated but empirically distinguishable dimensions. The framework further proposes two cross-cutting sub-dimensions that are especially salient for AI, as distinct from earlier technologies: perceived pedagogical value (a cognitive-evaluative judgement specific to instructional utility, distinguished from generic usefulness) and ethical-professional concern (an affective-cognitive hybrid capturing concerns about bias, integrity, data privacy, and professional identity). Their inclusion reflects the argument that AI-specific attitude scales cannot be adequately derived by simple substitution of 'AI' for 'computer' or 'technology' in legacy instruments; the construct itself has AI-specific content that must be independently theorised and sampled.

4.3 Behavioural Intention and Adoption

Consistent with the Theory of Planned Behaviour and TAM, attitude is theorised to act primarily through behavioural intention, moderated by perceived behavioural control and facilitating conditions, to produce actual classroom adoption behaviour. Adoption is not modelled as a terminal state but as a source of experiential feedback: successful, low-friction use of AI tools is expected to strengthen perceived usefulness and ease of use, while negative experiences—technical failure, perceived inaccuracy, or student misuse—are expected to



weaken affective components of attitude, illustrating the recursive, non-linear character of attitude change over the professional lifespan.

4.4 Implications for Measurement

The framework carries direct implications for the construction and standardization of attitude scales. First, item pools should be deliberately stratified across the cognitive, affective, and conative dimensions rather than dominated by any single dimension. Second, items addressing perceived pedagogical value and ethical-professional concern should be treated as conceptually distinct subscales rather than folded into general usefulness or affect items, since collapsing them risks attenuating discriminant validity. Third, contextual moderators identified in the antecedent layer—digital self-efficacy, institutional support, and prior experience—should be measured as covariates or correlates during scale validation to establish nomological validity, that is, to demonstrate that the new scale relates to established constructs in theoretically predictable ways. Fourth, given the rapid evolution of AI tools themselves, scale developers should anticipate the need for periodic re-standardization, since the object of attitude is not static in the way that, for example, attitude towards reading instruction has historically been.

5. Discussion

The framework proposed here departs from a purely technology-acceptance account in three respects. First, it foregrounds the ethical and professional-identity dimensions of AI attitude, which existing frameworks such as TAM and UTAUT, developed primarily for workplace productivity software, were not designed to capture. Second, it treats compatibility with professional pedagogical values, drawn from Diffusion of Innovations theory, as a first-order determinant of attitude rather than a peripheral moderating variable. Third, it explicitly models the recursive relationship between adoption experience and antecedent conditions, resisting the temptation to treat attitude as a fixed trait rather than a dynamic, experience-sensitive orientation.

The framework also carries implications beyond measurement. For teacher education, it suggests that interventions aimed at improving AI attitude should be multidimensional: addressing cognitive gaps through structured AI literacy training, affective concerns through supported, low-stakes experimentation, and conative barriers through institutional facilitating



conditions such as time allocation and technical support. A narrow focus on cognitive AI literacy training, without corresponding attention to affective and institutional conditions, is unlikely to produce durable attitude change or sustained adoption. For policy, the framework suggests that AI integration mandates unaccompanied by facilitating conditions—training, infrastructure, and time—risk generating attitude backlash rather than genuine acceptance, a risk borne out in prior research on top-down educational technology mandates more broadly. Certain limitations of the proposed framework should be acknowledged. As a theoretical synthesis, it has not yet been subjected to empirical test, and the relative weighting of its proposed dimensions—cognitive, affective, conative, pedagogical value, and ethical-professional concern—remains an open empirical question properly addressed through subsequent factor-analytic and validation research. The framework is also necessarily general; its application to specific teacher populations, such as pre-service B.Ed. trainees as distinct from in-service secondary teachers, may require dimension-specific elaboration, since pre-service teachers' attitude formation occurs prior to sustained classroom experience and may therefore weight cognitive and normative-social antecedents more heavily than experiential ones.

6. Conclusion

This paper has argued that the empirical measurement of teachers' attitudes towards artificial intelligence in education requires prior theoretical clarity about the structure of the attitude construct itself. By synthesising the Theory of Reasoned Action, the Theory of Planned Behaviour, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Rogers' Diffusion of Innovations, the paper has proposed an integrated conceptual framework organised around antecedent conditions, a tripartite cognitive-affective-conative attitude core augmented by AI-specific pedagogical-value and ethical-professional dimensions, behavioural intention, and adoption, connected through recursive experiential feedback. The framework is offered as a theoretical precursor to empirical scale construction and standardization efforts, with the intention of improving the content validity, dimensional clarity, and nomological grounding of instruments developed to measure this increasingly consequential construct in teacher education research.



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