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Optimizing Transactional Distance in Distance Education under Generative Artificial Intelligence Intervention—A Dual-Dimensional Framework of Dialogue Quality and Structural Flexibility

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Abstract: *Generative artificial intelligence (GenAI) is driving education toward a human–machine collaborative paradigm, reshaping teaching and learning interaction. In distance education, the separation of instructor and learner across time and space produces transactional distance—a psychological and communicative gap that constrains learning effectiveness—which neither classical theory nor conventional technology fully addresses in the intelligent era. Grounded in Moore's theory of transactional distance and drawing on Holmberg's guided didactic conversation, connectivism, and Vygotskian scaffolding, this study advances a conceptual framework explaining how GenAI regulates transactional distance through two mutually reinforcing pathways: strengthening dialogue quality and flexibilizing course structure. We construct a "technology–dimension–distance" dynamic model in which GenAI is the intervening variable, dialogue quality and structural flexibility are chain mediators, transactional distance is the outcome, and learner characteristics moderate the mediating paths. We articulate the internal mechanisms of this dual-path regulation, formalize the argument as testable propositions, and derive practical guidelines for dialogue design, structural flexibility, and ethical governance, offering actionable guidance for platform design, curriculum structuring, and resource allocation in intelligent distance education.*

Keywords: *generative artificial intelligence; distance education; transactional distance theory; educational interaction; dialogue quality; structural flexibility*

1. Introduction

The digital transformation of education has repositioned distance education from a peripheral mode of delivery to a central pillar of lifelong learning and mass higher education. Generative artificial intelligence (GenAI)---large language models and multimodal systems capable of natural-language understanding, dynamic content generation, and individualized adaptation---has accelerated this transformation, propelling pedagogy toward a human--machine collaborative model and reconstituting the interactive relationship between teaching and learning[7][19]. These capabilities offer unprecedented technological affordances for renewing distance education. Yet the defining characteristic of distance education---the separation of instructor and learner across time and space---continues to generate an enlarged transactional distance, leaving learners caught in a persistent tension between technological mediation and the relational essence of education.

Transactional distance, as formulated by Moore[9], is a psychological and communicative space of potential misunderstanding that arises when teacher and learner are separated, governed by the interplay of dialogue, structure, and learner autonomy. Rich dialogue and responsive structure contract this distance; sparse dialogue and rigid structure expand it. For decades this theory has anchored the instructional design of distance and online learning [20][16], but the classical model was developed for correspondence and broadcast media and does not readily explain the dynamic "dialogue–structure" relationship that emerges when an intelligent agent participates directly in the instructional transaction. GenAI does not merely transmit content or mediate dialogue—it generates dialogue, diagnoses cognition, and reconfigures structure in real time. Prior scholarship has documented individual technical applications—conversational agents, personalized recommendation, automated feedback—but has emphasized functional realization over integration with core educational theory, leaving the mechanism by which GenAI acts upon transactional distance insufficiently theorized.

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This study addresses that gap by asking, through Moore's theory, what mechanisms allow GenAI to regulate transactional distance, and how these mechanisms can be organized into a coherent model and translated into design principles. We argue that GenAI optimizes transactional distance through a dual-dimensional pathway—strengthening dialogue quality and flexibilizing course structure—with the two dimensions acting as chain mediators moderated by learner characteristics. On this basis we construct a "technology–dimension–distance" framework, formalize its claims as testable propositions, and derive practical guidelines for dialogue design, structural flexibility, and ethical governance. The contribution is threefold: theoretically, extending transactional distance theory into the generative-AI era; practically, guiding platform design, curriculum structuring, and resource allocation; and normatively, foregrounding the ethical boundaries needed to keep learners central to an increasingly automated interaction ecology.

2. Theoretical Foundations and Literature Review

2.1 Moore's Theory of Transactional Distance

Moore's theory of transactional distance is the most influential pedagogical theory of distance education. Moore[9] defined transactional distance as a psychological and communications space separating instructor and learner—a space of potential misunderstanding arising from physical separation rather than geography. Its magnitude is determined by three variables: dialogue, the purposeful, constructive interaction in which teacher and learner build on each other's contributions; structure, the rigidity or flexibility with which a program's objectives, strategies, and evaluation methods accommodate individual needs; and learner autonomy, the extent to which the learner rather than the instructor determines the goals, experiences, and evaluation of learning.

Moore's central proposition is functional: transactional distance is inversely related to dialogue and positively related to structure. As dialogue increases and structure becomes more responsive to individual needs, transactional distance decreases; as dialogue diminishes and structure hardens, it grows. This relationship is frequently expressed as the transactional-distance function:

$$TD = f(D, S) \tag{1}$$

Here D denotes dialogue and S denotes structure, the two determining dimensions. Moore [8] further distinguished three types of interaction—learner–content, learner–instructor, and learner–learner—that together constitute the dialogic fabric of distance learning, and Moore and Kearsley [10] subsequently embedded the theory within a systems view of online learning. The present study builds directly on this formulation, asking how a generative technology can simultaneously amplify the dialogue variable and soften the structure variable so as to shorten transactional distance and improve learning outcomes.

2.2 Complementary Theoretical Perspectives

Three additional lenses enrich the analysis. Holmberg's [4] theory of guided didactic conversation conceives of distance teaching as conversation-like rather than one-way transmission, later reframed [5] as grounded in empathy: feelings of rapport promote motivation and can be fostered through both simulated (internalized) and real, two-way communication—an emphasis directly relevant to GenAI systems capable of emotion-sensitive interaction [13]. Connectivism [12] reconceives learning as forming and traversing networks of people, information sources, and tools, in which GenAI functions as both node and navigator, expanding the learner's connective reach. The Vygotskian zone of proximal development and scaffolding [14] frame the AI tutor as a "more knowledgeable other" offering temporary, adaptive support that is withdrawn as competence grows. Finally, affective computing [11] supplies the technical foundation for the empathetic dialogue Holmberg's theory anticipates. Together, these perspectives position GenAI as an active pedagogical agent that can strengthen dialogue and reshape structure, framing the mechanism analysis that follows.

2.3 Prior Research and the Research Gap

A substantial body of empirical research confirms the explanatory power of transactional distance theory in technology-mediated settings: studies have validated the dialogue–structure–autonomy constructs in web-based environments [6], shown that technological features affect perceived distance and satisfaction [15], and demonstrated—especially during the COVID-19 transition to online learning—that structured design and sustained dialogue reduce transactional distance and enhance engagement, with social presence and autonomous motivation acting as mediators [3][2][21]. The scope of "dialogue" has also broadened from teacher–learner interaction to include learner–learner and learner–content interaction, with different forms argued to be partially substitutable [1].

In parallel, a rapidly growing literature documents AI applications in education, from adaptive tutoring toward autonomous content generation [17], and catalogues the affordances and risks of large language models for teaching, including personalized feedback and concerns about inaccuracy, over-reliance, and academic integrity [7]. Knowledge-graph-based systems increasingly support modular curricula and personalized paths [18], and multimodal models enable automated recognition of learners' emotional states. Two gaps remain, however: most studies address isolated functions—dialogue systems, recommendation, feedback—loosely coupled to educational theory; and work on dialogue quality and structural flexibility typically examines a single dimension, without linking both to transactional distance within an integrative "technology–dimension–distance" framework. This study responds to both gaps.

3. Mechanisms of Generative AI Intervention in Transactional Distance

Building on the theoretical foundations and the identified gap, this section develops a mechanism model of how GenAI regulates transactional distance through two levers---the strengthening of dialogue quality and the flexibilization of course structure---specifying the functional relationships and realization pathways of each, before analyzing their interaction.

3.1 Strengthening Dialogue Quality

GenAI strengthens dialogue quality along four dimensions—emotional connection, informational precision, feedback timeliness, and depth of guidance—acting on both the communicative and psychological components of transactional distance. First, drawing on affective computing, GenAI reinstantiates Holmberg's internalized dialogue by parsing learners' emotional states in real time and responding with empathetic language, and high-fidelity speech synthesis can emulate a teacher's prosody and warmth to heighten emotional resonance. Second, informational precision is achieved by coupling a learner model with knowledge-graph reasoning: the system diagnoses misconceptions, decomposes reasoning paths, and matches cognitive scaffolds to prior knowledge, generating hierarchically progressive dialogue scripts that operationalize scaffolding within the zone of proximal development.

Third, by providing round-the-clock, continuous dialogue, GenAI repairs the temporal ruptures of conventional distance education and enhances the continuity of teacher–learner dialogue. Fourth, depth of guidance and timeliness are secured through domain-specific deployment that performs semantic understanding, intent recognition, and response generation with minimal latency, while integrated multimodal output—text, speech, and dynamic visualization—accommodates learners' perceptual preferences, raising engagement and comprehension. Through these mechanisms GenAI directly compresses the communicative and psychological components of transactional distance: in Moore's terms it amplifies the dialogue variable, and, holding structure constant, higher dialogue implies shorter transactional distance.

3.2 Enhancing Structural Flexibility

Whereas dialogue works on the immediate transaction, structural flexibility works on the architecture of the course. GenAI enhances structural flexibility along four dimensions: modular adaptation, adjustable pacing, hierarchical objectives, and resource matching. Using knowledge graphs, GenAI performs semantic decomposition and relational modeling of core knowledge points, constructing a modular curriculum architecture that allows learners to select their own learning paths and thereby increasing the fit between course structure and individual cognitive characteristics [18]. A four-dimensional "objective--knowledge--competence--literacy" resource framework supports multidimensional, recombinable module orchestration.

Drawing on multi-source learning-behavior data, the system dynamically optimizes task-difficulty gradient, instructional pacing, and feedback intensity, realizing a closed-loop, teaching-determined-by-learning structural tuning. Based on assessments of learners' self-planning capacity, knowledge reserves, and higher-order-thinking maturity, GenAI can partition a three-tier objective system—foundational consolidation, capability transition, and innovative challenge—that responds to differentiated needs while preserving disciplinary integrity, and it intelligently pushes learning resources to improve their targeted-supply efficiency. In Moore's terms, these operations soften the structure variable: a program that would otherwise impose a single, rigid path becomes responsive to the individual, which—holding

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dialogue constant—reduces transactional distance.

3.3 The Coupling Mechanism between Dialogue Quality and Structural Flexibility

Dialogue quality and structural flexibility are not independent levers but a coupled, mutually reinforcing pair. Improvement in dialogue quality supplies the diagnostic information that structural adaptation requires; conversely, a modular, appropriately paced structure opens the pedagogical space for high-quality dialogue. Their relative strength varies by context—adult learners depend more on adjustable pacing, higher-order learners more on deep dialogic guidance—and by continuously sensing interaction outcomes, GenAI dynamically adjusts both to maintain equilibrium and continuous optimization of transactional distance. This coupling is the pivot of the dual-path model developed next: it explains why the two mediators must be theorized together, and why interventions targeting only one dimension yield sub-optimal results.

4. A Theoretical Model of AI-Mediated Transactional Distance Optimization

4.1 Core Variables and Their Relationships

The model comprises four classes of variables. The intervening variable is GenAI, whose core functions—dialogue generation and structural adaptation—are manifested as real-time response, emotion recognition, modular reconfiguration, and dynamic adaptation. The mediating variables are dialogue quality (emotional connection, informational precision, feedback timeliness, depth of guidance) and structural flexibility (modular adaptation, adjustable pacing, hierarchical objectives, resource matching). The outcome variable, transactional distance, is decomposed into communicative and psychological distance, both negative indicators. The moderating variable, learner characteristics, regulates the mediating paths through autonomy, learning style, and AI acceptance. Table 1 summarizes the constructs and their dimensions.

Table 1. Constructs and dimensions of the model.

Variable role	Construct	Dimensions
Intervening	Generative AI	Dialogue generation and structural adaptation (real-time response, emotion recognition, modular reconfiguration, dynamic adaptation)
Mediator 1	Dialogue quality	Emotional connection; informational precision; feedback timeliness; depth of guidance
Mediator 2	Structural flexibility	Modular adaptation; adjustable pacing; hierarchical objectives; resource matching
Outcome	Transactional distance	Communicative distance; psychological distance (both negative indicators)
Moderator	Learner characteristics	Autonomy / self-regulation; learning style; AI acceptance

The hypothesized relationships are as follows: GenAI exerts a significant positive influence on both dialogue quality and structural flexibility, each of which exerts a significant negative influence on transactional distance, functioning as chain mediators between GenAI intervention and outcome. Learner characteristics condition the adaptivity of the mediators—learners with higher self-regulation adapt more readily to flexibilized structure, and higher AI acceptance sharpens the psychological-distance-shortening effect of dialogue-quality gains.

4.2 The Dual-Path Model and Its Interpretation

As the core intervening variable, GenAI acts on transactional distance through two paths: directly, as affective and personalized interaction strengthens dialogue quality; and indirectly, as modular reconfiguration and dynamic adaptation optimize structural flexibility, creating adapted scenarios for high-quality interaction. Learner characteristics moderate both paths, jointly determining the degree of optimization achieved. The model can be summarized as a moderated chain: GenAI → dialogue quality and structural flexibility → reduced transactional distance, with learner characteristics moderating each

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link (see Figure 1). By integrating the technological, pedagogical, and learning dimensions into one structure, the model re-specifies Moore's TD = f(D, S) not as a static configuration but as a dynamic process in which an intelligent agent continuously tunes both determining dimensions.

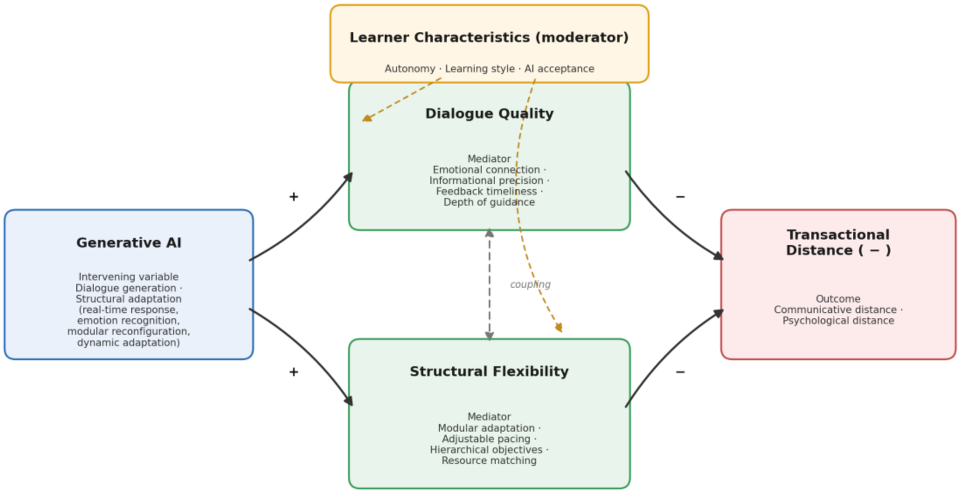

Figure 1. The dual-path model of GenAI-mediated transactional distance optimization.

4.3 Theoretical Propositions

To sharpen the model's logic and render it empirically testable, we formalize its claims as six propositions:

P1. GenAI intervention is positively associated with dialogue quality.

P2. GenAI intervention is positively associated with structural flexibility.

P3. Dialogue quality is negatively associated with transactional distance (both communicative and psychological).

P4. Structural flexibility is negatively associated with transactional distance.

P5. Dialogue quality and structural flexibility jointly mediate---in a chain---the relationship between GenAI intervention and transactional distance.

P6. Learner characteristics (autonomy, learning style, AI acceptance) moderate the mediated relationships, such that the distance-reducing effects are stronger for learners with higher self-regulation and higher AI acceptance.

These propositions convert the narrative mechanism into a set of falsifiable relationships that future empirical work---survey-based structural equation modeling, learning-analytics studies, or design-based experiments---can operationalize and test. Stating them explicitly also clarifies the model's boundary conditions: the framework predicts optimization of transactional distance only insofar as dialogue quality and structural flexibility are genuinely improved, and only to the degree that learner characteristics permit the mediators to operate.

5. Practical Guidelines for Optimizing Transactional Distance

From the model we derive three sets of design guidelines---for dialogue quality, structural flexibility, and ethical governance---that translate the mechanism analysis into actionable principles for platform designers, course developers, and institutions.

5.1 Dialogue Quality Optimization

Effective AI dialogue design should be governed by three coordinated principles. First, in keeping with Holmberg's guided didactic conversation, affective computing should let the AI recognize, understand, and respond to learners' emotions, replacing formulaic replies with empathetic interaction. Second, coupling the learner's profile with a structured knowledge graph, the system should dynamically

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generate guidance paths fitting developmental stage, knowledge reserve, and stylistic preference, ensuring reasonable problem gradients and on-target feedback. Third, the AI must remain a facilitator rather than a substitute, offering just-enough intervention at key cognitive junctures to safeguard autonomous construction and critical thinking—an especially important safeguard given documented risks of over-reliance and "metacognitive laziness," since scaffolding must fade as competence grows. Together these principles point toward a learner-centered ecology of intelligent educational dialogue.

5.2 Structural Flexibility Design

Course design should follow three core principles. Modular decomposition divides instructional units according to the internal logic of the knowledge and the laws of cognitive development, so that each module remains relatively independent yet organically linked, preserving structural elasticity without sacrificing disciplinary integrity. Adaptive regulation relies on an AI-driven feedback mechanism that collects and interprets learning-behavior traces in real time to optimize pace, difficulty gradient, and resource matching. Hierarchical adaptation recognizes differences in self-directed learning capacity and prior knowledge, offering three channels—foundational consolidation, capability enhancement, and higher-order challenge—for diverse developmental needs. Together these principles operationalize the softening of structure, increasing responsiveness to the individual without dissolving curricular coherence.

5.3 Ethical Boundaries

Because GenAI acts directly on the learner, its deployment must be bounded by three ethical principles. Privacy protection requires full-lifecycle governance of learning data—encryption and permission isolation at collection and storage, and auditable, scenario-specific authorization at use—to foreclose information leakage. Safeguarding learner subjectivity keeps the learner at the center of cognitive activity through explainable interaction and controllable interfaces, guarding against the alienation that technological dominance can produce. Humanistic care closes the gap between technological rationality and educational warmth by injecting value guidance and developmental encouragement alongside empathetic response. These boundaries are not external constraints but constitutive conditions of legitimate optimization: transactional distance reduced at the cost of privacy, agency, or dignity would be a false economy.

6. Discussion

The framework advanced here makes three contributions. Theoretically, it extends Moore's transactional distance theory into the era of generative intelligence: whereas the classical model treats technology as a medium, our model treats GenAI as an active participant that generates dialogue and reconfigures structure in real time, re-specifying TD = f(D, S) as a dynamic, AI-mediated process. Theorizing dialogue quality and structural flexibility as chain mediators rather than parallel factors also clarifies why single-dimension interventions underperform: the two are coupled, and their equilibrium sustains distance reduction. This integrative move responds directly to the fragmentation of the existing literature.

The framework also reframes familiar debates. The concern that automation erodes the human relation in education is addressed not by resisting AI but by specifying the conditions—empathetic dialogue, measured intervention, preserved autonomy—under which AI can shorten psychological distance without displacing the learner as subject. The documented risk of over-reliance and metacognitive laziness is accommodated as a boundary condition: dialogue-quality gains reduce transactional distance only when scaffolding fades appropriately and autonomy is protected. Practically, the model offers a design vocabulary: the four dimensions of each mediator become concrete design targets, and the moderating role of learner characteristics motivates adaptive personalization—more deep dialogic guidance for higher-order learners, more adjustable pacing for adult learners. Because each relationship is a directional, testable claim, the model can be operationalized through structural equation modeling, learning-analytics measures, or design-based experiments that observe effects on validated transactional-distance instruments.

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7. Conclusion, Limitations, and Future Research

This study set out to explain how generative AI can optimize transactional distance in distance education and to organize that explanation into a coherent, testable framework. Grounding the analysis in Moore's theory and drawing on Holmberg's guided didactic conversation, connectivism, scaffolding, and affective computing, we argued that GenAI regulates transactional distance through a dual-dimensional pathway—strengthening dialogue quality and flexibilizing course structure—formalized as a "technology–dimension–distance" model in which the two dimensions act as chain mediators, learner characteristics moderate the paths, and transactional distance is the outcome. From the model we derived practical guidelines for dialogue design, structural flexibility, and ethical governance, and stated six propositions to guide empirical testing.

The study has limitations. As a conceptual contribution it is not yet empirically validated; the proposed relationships, though grounded in established theory and evidence, await direct measurement. The framework abstracts across educational levels and disciplines, and the relative weight of the two pathways likely varies in ways specified here only qualitatively. The moderating set of learner characteristics is not exhaustive—motivation, digital literacy, and cultural context may also matter—and the rapid evolution of GenAI capabilities means the functional affordances assumed here will require periodic re-specification.

Future research should proceed on three fronts: empirical validation through structural equation modeling, learning analytics, and design-based experiments operationalizing the propositions; differentiated modeling across contexts—adult, higher, and K-12 education; high- and low-structure disciplines—to refine the weighting of the two pathways; and longitudinal, ethical inquiry into the long-term effects of AI-mediated interaction on learner autonomy, ensuring shorter transactional distance continues to serve rather than supplant the developmental essence of education.

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