

Quantum Dialogism: A Quantum-Like Modelling Proposal for AI-Mediated Dialogic Learning

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DOI: <https://doi.org/10.51584/IJRIAS.2026.11090030>

Received: 17 September 2026; Accepted: 22 September 2026; Published: 09 October 2026

ABSTRACT

Dialogic pedagogy treats learning as an encounter among perspectives in which difference is productive rather than merely erroneous. Learner models in computer-supported collaborative learning (CSCL), however, have commonly been designed to predict performance or estimate mastery. They are not generally designed to represent the changing relations among the interpretive positions that learners articulate in dialogue. This conceptual paper introduces Quantum Dialogism, a cautious quantum-like modelling proposal for this representational problem. The proposal does not claim that learners, groups, or large language models (LLMs) are physical quantum systems, nor does it claim that dialogic constructs are mathematically isomorphic to quantum-mechanical constructs. Rather, it identifies four theoretically motivated correspondences—multi-voicedness and state superposition, meaning made through juxtaposition and interference, pedagogical sequencing and non-commutativity, and distributed dialogue and non-separable group states—and specifies the empirical conditions under which each could be modelled or rejected.

The paper makes four contributions. First, it distinguishes a metaphorical use of quantum language from a formal quantum-like learner model. Second, it provides a minimal operational specification: a task-defined voice codebook, state construction, positive-operator-valued measurements, sequential update rules, and parameter estimation. Third, it places the proposal against appropriate classical alternatives, including Bayesian knowledge tracing, multidimensional cognitive-diagnostic models, mixture models, and dynamic Bayesian networks. The issue is therefore not whether classical probability is intrinsically incapable of representing dialogic learning, but whether a quantum-like model offers a more parsimonious or predictively useful account of specified contextual and order-dependent phenomena. Fourth, it proposes preregisterable hypotheses, evaluation criteria, and explicit failure conditions. LLMs are treated as configurable mediating artefacts whose outputs can widen, narrow, or structure a dialogic space; they are not treated as conscious participants. The resulting framework is a falsifiable research programme for evaluating whether quantum-like representations add explanatory value to AI-mediated dialogic learning.

Keywords: dialogic pedagogy; learner modelling; quantum cognition; generative artificial intelligence; large language models; computer-supported collaborative learning; contextuality; dialogic space.

INTRODUCTION

Dialogic pedagogy regards learning as more than an individual accumulation of propositions or skills. It arises through the encounter of perspectives, questions, and responses. In this tradition, the difference between voices is not a defect to be eliminated; it can become a resource for inquiry, creativity, and revised understanding (Bakhtin, 1981, 1984; Koschmann, 1999; Mercer et al., 2019; Wegerif, 2007, 2013; Wegerif & Yang, 2011). In CSCL, this claim has an important computational consequence. A learner model that records only a probability of correct performance may be useful for prediction while remaining silent about the competing interpretations, source positions, and interactional sequences through which understanding develops.

This observation does not establish that existing learner models are inadequate in general. Bayesian knowledge tracing (BKT) was designed to track knowledge acquisition at the level of specified skills (Beck & Xiong, 2013; Corbett & Anderson, 1994), and a substantial family of classical approaches can represent heterogeneity, multiple dimensions, temporal dependence, and contextual covariates. Examples include cognitive-diagnostic models, mixture models, multidimensional item-response models, hidden Markov models, and dynamic Bayesian networks (De la Torre, 2009; Käser et al., 2017; Rupp et al., 2010). These approaches should be treated as serious comparators, not as straw alternatives. The narrower question addressed here is whether a quantum-like probability model can supply an empirically useful representation when a learning task produces **contextual, order-dependent, and potentially non-separable interpretive responses** that classical models represent less parsimoniously or predict less accurately.

Quantum cognition is relevant because it uses the mathematical apparatus of quantum probability to model cognitive phenomena such as question-order effects, contextuality, and interference without asserting that cognition is physically quantum (Aerts, 2009; Busemeyer & Bruza, 2012; Khrennikov, 2015; Pothos & Busemeyer, 2013; Trueblood & Busemeyer, 2011; Wang et al., 2014). A quantum-like model is implemented on ordinary digital hardware. Its potential value lies in its representational commitments, including state vectors or density matrices, incompatible measurements, and context-sensitive sequential updates. It does not follow that every conceptual contrast in education warrants a quantum-like model. The relevant evidence must come from tasks in which these commitments yield clear, discriminating predictions.

The present paper therefore reformulates the earlier idea of Superposed Voices as a **theoretically motivated modelling proposal**, rather than as an established mathematical equivalence between dialogism and quantum mechanics. It concentrates on three questions. First, what would a defensible quantum-like representation of dialogic learner states require? Second, how would it differ empirically from well-specified classical alternatives? Third, how can the proposal be falsified? Addressing these questions allows the framework to retain its conceptual ambition while making its epistemic status explicit.

Scope, Terminology, and Claims

Dialogic Learning as the Target Phenomenon

In this paper, a voice is not a person, an inner essence, or a fixed identity. It is an interpretive position that can be expressed, attributed, taken up, resisted, or transformed within a bounded learning task. A learner discussing a historical controversy, for example, may articulate an evidential voice, an ethical voice, a disciplinary voice, and a pragmatic voice. The analytic aim is not to infer a complete psychology from these utterances. It is to model how task-defined positions are activated and how their relation changes after particular dialogic moves.

This definition is consistent with Bakhtin's account of polyphony and with later accounts of dialogic space, but it does not reduce those philosophical traditions to a formal model. The model captures only a limited empirical slice: observable or elicited responses to defined interpretive positions in a specified task. It cannot prove that meaning is exhausted by those responses, and it cannot replace qualitative analysis of dialogue.

Three Levels Of Assertion

The paper separates three levels that are often conflated in interdisciplinary work.

Empirical claims concern observable regularities, such as a replicated question-order effect or a difference in predictive performance between models. They require data, measurement reliability, and statistical analysis.

Formal claims concern the adequacy of a specified mathematical model. They require explicit state spaces, measurement operators, update rules, and estimation procedures. A formal claim can be assessed even when its theoretical interpretation remains disputed.

Theoretical and pedagogical claims concern whether a formal model offers a useful interpretation of dialogue and whether an intervention is educationally desirable. These claims are supported by coherence with theory and, where available, intervention evidence. They are not established merely because an evocative mathematical analogy exists.

Accordingly, terms such as superposition, interference, collapse, entanglement, and uncertainty are used below in one of two restricted senses. They refer either to defined features of a quantum-like probability model or to clearly labelled pedagogical analogies. They are never offered as literal applications of microscopic quantum mechanics to classrooms, brains, or LLMs.

A Bounded Account of Classical Alternatives

A conventional scalar BKT model cannot, by itself, represent all aspects of dialogic learning because it was not designed to do so. Yet this limitation does not generalise to all classical probability. A latent-class mixture model can represent distinct response profiles. A multidimensional cognitive-diagnostic model can represent several skills or conceptions. A dynamic Bayesian network can represent dependencies among multiple latent variables and changes over time. Social-influence and multilevel models can represent interdependence among learners. Classical models may therefore explain many patterns that a quantum-like model could also fit. Quantum Dialogism makes a comparative, not a categorical, claim. It proposes that a quantum-like representation may be preferable **only if** it improves out-of-sample prediction, model parsimony, or process explanation for preregistered phenomena involving context and sequence. The proposal is unsupported when appropriate classical models provide an equal or better account.

From Correspondence to Formal Model

The four correspondences

Table 1 presents the framework's central correspondences. None is asserted to be an isomorphism. Each becomes a formal claim only after an operational definition and a discriminating test are supplied.

Table 1. Theoretically motivated correspondences and their empirical requirements

Dialogic construct	Quantum-like construct	Restricted interpretation	modelling	Minimum empirical requirement
Multiple interpretable positions	Superposed mixed state	or	A learner's task-specific state may encode more than one elicitable position before a response is requested.	Reliable voice coding and evidence that a coherent model improves on a classical mixture model.
Meaning through juxtaposition	Interference term	Combining two perspective prompts may change an outcome beyond a specified additive or mixture baseline.		Predefined contrast task, repeated measurement, and an estimated interaction that predicts held-out outcomes.
Context and instructional sequence	Non-commuting measurements	The response to a second prompt may depend on which prompt was administered first.		Randomised order manipulation and a replicated, model-discriminating order effect.
Shared dialogic space	Non-separable group state	A joint group representation may predict coordinated responses beyond independent individual-state models.		Comparison with multilevel, social-influence, and shared-context baselines; behavioural coupling alone is insufficient.

The distinctions in Table 1 prevent a familiar conceptual error. A productive contrast between views is not automatically quantum interference. A sequence effect is not automatically non-commutativity. Correlated learners are not automatically entangled. Each label earns its use only through an operationally specified model and a comparison against plausible alternatives.

Defining the Voice Space

Let a bounded learning activity define a finite set of K task-relevant interpretive positions, denoted by $V = \{v_1, \dots, v_k\}$. The positions should be derived from a transparent codebook that combines domain expertise, pilot interviews, and analysis of learner discourse. The codebook might distinguish, for example, evidence-based, intuitive, counterfactual, and ethical responses to a socio-scientific problem. Its adequacy should be assessed through inter-rater agreement, construct validation, and sensitivity to alternative coding schemes.

For an initial model, these positions can be represented by an orthonormal basis $\{|v_1\rangle, \dots, |v_k\rangle\}$ in a Hilbert space $\mathcal{H}$. This orthogonality is an **analytical simplifying assumption**, not a substantive claim that real voices are naturally independent, mutually exclusive, or psychologically pure. It means only that the coding scheme is treating the selected positions as distinguishable measurement categories for this task. If pilot data show overlapping positions, the model should use non-orthogonal effects or an alternative representation rather than impose orthogonality for convenience.

A learner i at time t may be represented by a density matrix ρ_{it} , a positive semidefinite matrix with trace one. The density-matrix form is preferable to a state vector because it can represent both a coherent state and an ordinary probabilistic mixture. A classical mixture over voice categories has a diagonal form:

$$\rho^{(\text{mix})}_{it} = \sum_{k=1}^K p_{ikt} |v_k\rangle\langle v_k|.$$

A quantum-like model allows off-diagonal terms. Those terms do not by themselves prove that a learner “holds incompatible ideas simultaneously.” Their value is strictly empirical: they can influence predicted probabilities under later contextual measurements. If the off-diagonal terms do not improve prediction or do not replicate, a diagonal mixture is the appropriate representation.

Measurements and Observable Outcomes

A learning event is represented by a measurement $M^{(c)}$ indexed by context c , such as a prompt, peer contribution, scaffold, or assessment item. A practical implementation may use a positive-operator-valued measure (POVM), $\{E^{(c)}_y\}$, where each effect corresponds to an observable response category y . These categories could include a selected interpretation, a coded dialogic move, a confidence judgement, a quality rating, or a transfer response. The model predicts:

$$P(Y = y \mid \rho_{it}, c) = \text{Tr}(\rho_{it} E^{(c)}_y).$$

This formulation requires the researcher to state what is measured and how. It does not allow “meaning in the gap” to be inserted after the fact as an unmeasured residual. If the outcome is a coded dialogic move, the coding protocol, coder training, reliability statistic, missing-data rules, and unit of analysis must be reported. If the outcome is learning, the assessment must be independently scored or pre-registered before fitting the model.

Interference as a Testable Residual, Not a Synonym For Meaning

Suppose a learner receives a prompt that presents interpretive position a , position b , or a deliberately designed juxtaposition of both. A quantum-like amplitude model may predict a target response probability of the form:

$$P(y \mid a \vee b) = pP(y \mid a) + (1 - p)P(y \mid b) + 2\sqrt{p(1 - p)P(y \mid a)P(y \mid b)} \cos(\phi_y).$$

where ϕ_γ is a fitted phase parameter. The final term is an interference term. In the proposed research programme, it is an estimate of a context-sensitive deviation from a pre-specified mixture baseline; it is **not** a direct measurement of dialogic meaning. A theoretically useful result would require the term to be stable across comparable tasks, to improve held-out prediction, and to be linked cautiously to independently coded forms of productive juxtaposition. A null or unstable term would count against this component of the model.

Sequential Updates and Order Effects

For a sequence of pedagogical events a then b , a projective approximation uses operators P_a and P_b . The probability of a response after the sequence is determined by the ordered product of those operators. If $P_a P_b \neq P_b P_a$, the sequence is non-commutative. In educational terms, this is a model of a specific possibility: asking learners first to articulate a peer's position and then to state their own position may yield a different distribution of responses than the reverse order.

The relevant claim is not that teaching “violates the uncertainty principle.” The relevant claim is that a specified order manipulation produces a reproducible pattern that is better described by incompatible contextual measurements than by a classical transition model with comparable flexibility. The comparison must include a dynamic Bayesian or hidden Markov baseline with order as an explicit covariate. Otherwise, a fitted non-commuting model may simply redescribe an ordinary sequencing effect.

Group-Level States

For a group of learners, a joint representation can be written in $\mathcal{H}_1 \otimes \cdots \otimes \mathcal{H}_n$. A separable state can be represented as a mixture of products of individual states. A non-separable state cannot. This vocabulary may be useful when a jointly constructed response cannot be predicted from individual elicited positions and documented shared task conditions. It is a demanding claim. Shared materials, common instruction, homophily, turn-taking, and direct social influence can all create correlation without non-separability.

Consequently, group-level Quantum Dialogism should be regarded as a later-stage research question. It should be tested against multilevel models, actor-oriented network models where appropriate, and dynamic social-influence models. The framework does not use entanglement as a rhetorical description of collaboration. The term is reserved for a model comparison in which a non-separable state gives a replicable advantage over those alternatives.

Large Language Models as Dialogic Mediating Artefacts

Generative AI can be designed to introduce contrasting explanations, invite learners to justify a position, summarise a disagreement, or prematurely close inquiry by producing an authoritative answer. These are pedagogically important functions and align with broader discussions of opportunities and risks in educational uses of LLMs (Kasneci et al., 2023). They do not establish that an LLM is a dialogic consciousness, nor that the model literally occupies a quantum superposition.

An LLM produces text from a conditional probability distribution shaped by its training, system instructions, retrieved context, prompt, and sampling settings. For the purposes of this framework, it is best understood as a **configurable mediating artefact**. A prompt can be designed to solicit alternative positions, but the resulting output remains an artefact to be interpreted, challenged, sourced, and evaluated by learners and teachers. Calling an LLM “polyphonic” is therefore a literary or pedagogical description of the plurality it can simulate, not a claim about its ontology.

This reframing improves the empirical design. The AI configuration becomes part of the intervention and must be reported: model name and version, system prompt, retrieval sources, temperature or equivalent sampling parameters, moderation settings, timing, and any human oversight. A study comparing dialogic and answer-first AI prompts should archive the exact prompt templates and a representative output sample. Without this information, an observed effect cannot be attributed meaningfully to a dialogic design feature.

Productive Ambiguity Without Quantum Uncertainty

Educational dialogue often benefits when learners encounter unresolved alternatives and must evaluate evidence before reaching a conclusion. This pedagogical condition may be called productive ambiguity. It should not be equated with Heisenberg's physical uncertainty relation. The construct can be studied with established educational measures, including the quality of explanations, epistemic cognition, transfer performance, and coded dialogic moves.

An LLM-supported prompt may therefore be designed to present two evidenced positions, ask a learner to identify their assumptions, request a counterargument, and require a warranted synthesis. Such a prompt can preserve inquiry without implying that the learner's knowledge state has literally collapsed. Whether it improves learning is an empirical question for a controlled intervention, not a conclusion supplied by the quantum-like vocabulary.

Human Agency and Consciousness

The framework neither requires nor settles a theory of consciousness. Existing indicator-based assessments conclude that contemporary AI systems are not strong candidates for consciousness under the selected indicators, while also noting that future systems could differ (Butlin et al., 2023). This is relevant to responsible educational framing, but it does not justify a categorical metaphysical boundary between human consciousness and every conceivable AI system.

The pedagogical implication is modest and practical: current LLM outputs should not be treated as evidence of understanding, intention, moral responsibility, or lived experience. Learners and educators remain responsible for interpretation, source evaluation, consequential decisions, and the social conditions of dialogue. The framework therefore distinguishes three propositions: the empirical assessment of current system indicators; philosophical views about the conditions of dialogue; and design choices about how an educational tool should be positioned. These propositions should not be treated as if one establishes the others.

Cognitive Bias, Prompting, and Dialogic Safeguards

Generative AI may make it easier to access alternative explanations, but fluent output can also create unwarranted confidence. Confirmation bias, automation bias, anchoring, and fluency-based truth judgements are plausible risks in AI-supported learning (Nickerson, 1998; Parasuraman & Riley, 1997; Reber & Schwarz, 1999; Skitka et al., 1999). They do not require a quantum-like explanation. They require design safeguards.

Four safeguards follow from the dialogic aim. First, prompts should require a learner to state an initial reason before receiving generated alternatives, so that change in position is visible rather than concealed. Second, the system should present traceable sources or flag unsupported claims where feasible. Third, learners should be asked to generate or assess counterarguments rather than merely select the most fluent answer. Fourth, consequential judgements should include peer or teacher review, especially where an AI output is treated as evidence. These safeguards create measurable intervention features. A study can compare an answer-first condition with a contrast-and-justify condition, then examine not only performance but also revision quality, source evaluation, distribution of dialogic moves, and overreliance on incorrect AI suggestions. The quantum-like model is useful only if it adds value to explaining these measures beyond standard intervention and learner-modelling analyses.

An Empirical Programme for Quantum Dialogism

Research Design and Data Structure

A first evaluation should focus on a single, bounded domain in which competing interpretations can be defined without forcing false equivalence. Suitable domains include evidence-based reasoning about

historical sources, scientific explanation of competing mechanisms, or ethical reasoning about a well-specified case. The study should develop a voice codebook through pilot work, preregister the retained categories, and publish examples of included and excluded utterances.

A multi-session design could randomly assign learners to one of two AI-mediated conditions: an answer-first condition that gives an explanatory response and a dialogic condition that presents contrasting positions, requests justification, and sequences prompts deliberately. Within condition, selected prompt orders can be randomised. Repeated individual responses, discourse traces, and independent post-test measures should be collected. Group-level analyses should only be attempted where interactions occur in genuine groups and where individual pre-interaction measures are available.

The primary outcomes should include one learning measure external to the model, such as transfer or quality of explanation, and one process measure, such as a validated dialogic coding scheme. When discourse coding is used, the study should report the coding manual, coder independence, reliability statistic and confidence interval, unitisation rules, treatment of disagreement, and any machine-assistance procedure. A transparent dialogic coding framework may be adapted, but adaptation requires renewed validation rather than a mere label transfer (Hennessy et al., 2016).

Competing Model Families

A valid test does not compare a quantum-like model only with a scalar BKT implementation. Table 2 specifies a minimum comparison set. All models should have access to the same training data and relevant covariates. Hyperparameter selection must be nested within training folds to prevent optimistic comparisons.

Table 2. Minimum model-comparison set

Model family	What it can represent	Role in the comparison
Bayesian knowledge tracing	Skill-level temporal mastery under a hidden Markov assumption	Establishes a conventional skill-tracing baseline.
Multidimensional cognitive-diagnostic or item-response model	Multiple latent attributes or continuous dimensions	Tests whether simultaneous-looking positions are adequately represented by multiple classical traits.
Latent-class or mixture model	Heterogeneous response profiles and probabilistic switching	Tests whether a classical mixture explains apparent plurality without coherence terms.
Dynamic Bayesian network / hidden Markov model	Time, covariates, transitions, and ordered dependencies	Tests whether order effects are explained by classical state transitions.
Multilevel or social-influence model	Group dependence, shared context, and peer effects	Tests group-level claims before considering non-separable states.
Quantum-like density-matrix model	Contextual measurements, sequential incompatibility, and off-diagonal coherence	Tests the specific additional commitments of Quantum Dialogism.

Parameter Estimation and Model Checking

The quantum-like model may be fit using Bayesian hierarchical estimation or regularised maximum likelihood. Learner-level states and measurement effects should be partially pooled so that sparse learner histories do not produce unstable individual estimates. Priors or penalties should favour low-rank and near-diagonal states unless the data justify added coherence. This is important because an unconstrained quantum-like model can become more flexible than a classical comparator and win for the wrong reason.

Parameters should be interpreted cautiously. A non-zero off-diagonal term is not evidence of a lived internal contradiction. It is evidence only that the term improved the fit to specified response data under the model. Posterior predictive checks should assess whether each model reproduces observed response distributions, order effects, and individual trajectories. Convergence diagnostics, parameter recovery on simulated data, sensitivity to the voice codebook, and robustness to alternative priors are necessary before substantive interpretation.

Preregistered Hypotheses and Decision Criteria

Table 3 provides a template rather than a claim that these hypotheses are already supported. A registered report or public preregistration should fix the task, codebook, exclusions, primary outcomes, model families, and analytic decision rules before examining outcome data.

Table 3. Illustrative preregistered hypotheses and failure conditions

Hypothesis	Predicted observable pattern	Primary comparison	Result that counts against the framework
H1: Contextual juxtaposition	A contrast prompt produces a response distribution not captured by the preregistered classical mixture baseline.	Quantum-like model versus mixture and multidimensional models.	No replicated predictive advantage, or the apparent effect disappears after classical context covariates are added.
H2: Sequencing	Prompt order changes a specified judgement or dialogic move.	Non-commuting update model versus dynamic Bayesian / hidden Markov model with order effects.	No replicated order effect, or a classical transition model predicts it as well or better.
H3: Instructional usefulness	The dialogic AI condition improves transfer or explanation quality without increasing uncritical AI reliance.	Multilevel intervention analysis with condition and baseline covariates.	No practically meaningful outcome advantage, or gains are offset by poorer source evaluation.
H4: Group representation	A joint state predicts post-interaction group responses beyond individual states and social-influence baselines.	Non-separable model versus multilevel and social-influence models.	The joint model does not improve held-out prediction or the dependence is explained by shared context.

The primary model-selection criterion should be held-out expected log predictive density or an equivalent predictive score, accompanied by calibration, Brier scores for categorical outcomes, and complexity-sensitive comparison such as leave-one-out cross-validation. Bayes factors, WAIC, or information criteria may be reported as secondary evidence where assumptions permit, but no single statistic should determine

the conclusion. Educational significance also matters: an improvement should be interpreted alongside effect sizes and the consequences of model error.

The framework is unsupported for a target phenomenon when a well-specified classical model has equal or better held-out performance, when a proposed quantum-like parameter is non-identifiable or unstable, when posterior predictive checks fail, or when the predicted context and order patterns do not replicate. These are substantive outcomes, not failures of implementation to be concealed by more elaborate metaphor.

Evidence Boundary for Previous Work

Earlier design-based work on AI-mediated dialogue can motivate the present programme by showing that dialogic prompts and discourse coding are feasible. It does **not** validate Quantum Dialogism unless the study itself defines the state space, measures the relevant outcomes, fits the competing models, and reports the comparison described above. For that reason, this paper does not treat prior forum analyses or improvements in dialogic codes as confirmation of the proposed quantum-like representation. Any future manuscript that uses such data as evidence should provide the sample and setting, intervention sequence, exact AI configuration, coding reliability, classifier performance if automation is used, statistical tests, effect sizes, attrition, and limitations.

DISCUSSION

Quantum Dialogism offers a vocabulary for asking a precise modelling question: when learners respond to alternative positions in context, does a quantum-like representation describe their responses more usefully than classical alternatives? The proposed answer is deliberately conditional. A Hilbert-space representation is not warranted by the fact that dialogue is complex, and a compelling analogy is not an empirical result. The value of the framework lies in converting a broad philosophical intuition about multi-voicedness into a transparent sequence of modelling and design decisions.

The proposal also clarifies what is and is not at stake. Classical learner models are not dismissed. They can represent more than scalar mastery, and many educational patterns will be better served by classical models that are easier to estimate and explain. A quantum-like model earns adoption only by offering a stable, parsimonious, and externally useful account of preregistered contextual phenomena. Conversely, classical models should not be defended by assuming that conceptual plurality is always reducible to independent dimensions. The comparison is empirical.

The approach has several limitations. First, a codebook inevitably simplifies discourse. A task-defined voice category is an analytic handle, not an exhaustive account of a learner's social positioning or lived experience. Second, model comparisons can be distorted by unequal flexibility, sparse data, or outcome measures that fail to register the process of interest. Third, interpretations that borrow the language of quantum theory may appear more precise than the available data warrant. These risks motivate the constraints proposed here: explicit measurement, parameter recovery, matched baselines, public materials, and failure conditions.

For educational practice, the paper supports a conservative conclusion. LLMs can be designed to sustain inquiry by making perspectives visible, requesting reasons, exposing uncertainty in claims, and inviting learners to compare sources. These practices do not depend on claims of AI consciousness or physical quantum processes. They depend on careful pedagogical design and human accountability. The quantum-like model, if future evidence supports it, would be a tool for analysing selected response patterns within such environments; it would not replace the ethical, social, and interpretive work of teaching.

CONCLUSION

This paper has reframed Quantum Dialogism as a cautious and testable research programme. The framework proposes correspondences between dialogic pedagogy and quantum-like cognition, but it does not claim established isomorphism, literal quantum mechanics in education, or a demonstrated advantage over

classical learner modelling. Its formal core comprises task-defined voice categories, learner-state representations, context-sensitive measurements, sequential update rules, and direct comparison with classical alternatives.

The next step is not further conceptual amplification. It is empirical discipline: develop valid voice measures, randomise context and sequence, archive AI configurations, compare matched models, and report negative findings. If a quantum-like model improves prediction and explanation under these conditions, it may offer a useful addition to CSCL learner modelling. If it does not, the dialogic theory remains valuable while the quantum-like formalism should be narrowed or rejected for that purpose. This is the appropriate standard for a framework that seeks to bridge philosophical theory, educational design, and mathematical modelling.

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