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DIDACTIC CONDITIONS FOR APPLYING DYNAMIC ARTIFICIAL INTELLIGENCE MODELS IN PREPARING STUDENTS FOR INTERNATIONAL STANDARDIZED EXAMINATIONS

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ABOUT ARTICLE

Key words: dynamic artificial intelligence models; didactic conditions; competence-based approach; individualization; zone of proximal development; international standardized examinations; diagnostic monitoring; TPACK; andragogy; Bloom's taxonomy.

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Abstract: Artificial intelligence now forecasts examination outcomes faster than pedagogy has learned to use those forecasts well. This study asks a narrower question: what has to be true for a dynamic AI model to teach, not merely predict, when preparing students for the SAT, ACT, GRE, and GMAT? Drawing on Vygotsky's zone of proximal development, the TPACK framework, Bloom's taxonomy, and Knowles' andragogy, the analysis ties a diffusion-type stochastic model, based on a generalized Ornstein-Uhlenbeck process, to four conditions: continuous diagnostic monitoring, individualized content and pace, teacher readiness to interpret the model, and learner reflexive-regulatory competence. Each condition anchors to a distinct term in the same governing equation, which links pedagogical theory and mathematical formalism in a way not previously made explicit. Four limitations are

named, and a testable hypothesis closes the paper.

Introduction. Predictive AI systems are no longer a novelty in education research; they already sit inside classrooms and admissions offices [1]. What has not caught up is the didactic side. A model can call a student's SAT score within a few points and still teach that student nothing, if no one has worked out how the forecast should change tomorrow's lesson. This study asks the second question, not the first: under what conditions does using a dynamic AI model actually teach something?

The stakes are concrete. More students in Uzbekistan sit the SAT, ACT, GRE, and GMAT each year, aiming for universities abroad. These exams can be retaken, unlike a census-style national assessment, which is exactly why individualized forecasting matters here: a retake only helps if preparation changed between attempts. Most existing tools were built by people optimizing for accuracy rather than for teaching, leaving a technology whose statistics are well understood and whose classroom use is not.

The author's earlier work built the mathematical apparatus for this kind of forecasting [5; 6] and separately reviewed how interpretable prediction has served pedagogical diagnostics [7]. A parallel study outside this program reached a similar verdict from the machine-learning side [8]: technical work has outrun pedagogical work. Neither strand explains when a mathematically sound model becomes a pedagogically sound practice. That gap is this article's subject.

The purpose is to establish, on theoretical grounds, the didactic conditions dynamic AI models must satisfy to be pedagogically effective in this context. Four objectives follow: clarifying what “didactic conditions” means for such models; establishing how the model's mathematical parameters relate to didactic requirements; identifying and justifying the conditions themselves; and formulating a hypothesis for later experimental testing.

The object is the process of preparing students for international standardized examinations under AI deployment; the subject is the didactic conditions governing that deployment.

Scientific novelty. Existing work on AI in test preparation either offers general advice on “using technology well” or stays inside the mathematics, refining prediction without asking what it is for — including the author's own prior papers, which built the apparatus but not the pedagogy. This study treats didactic conditions differently: not a checklist borrowed from technology-integration literature, but a structure tied to a specific equation. Each condition corresponds to a distinct term in that equation; remove one, and a specific link between model and classroom breaks. That correspondence, not the conditions in isolation, is the new part.

Practical significance. Teacher-training programs and institutions procuring AI diagnostic tools can use the four conditions as a deployment checklist: not simply “add AI,” but add it under these four arrangements, with the diagnostic instruments the analysis implies.

Materials and Methods. The design is deductive-theoretical. No new data were collected; the core task is establishing a structural link between existing psychological-pedagogical theory and a mathematical model already built within this research program. That choice needs defending, since arguing from a model rather than a dataset is not the field's default move. A dynamic model of knowledge accumulation is, at bottom, a hypothesis about mechanism: how competence should move over time under given influences. Testing whether that hypothesis is pedagogically sound means first working out what it implies for practice. Figure 1 sets out the six stages of that work.

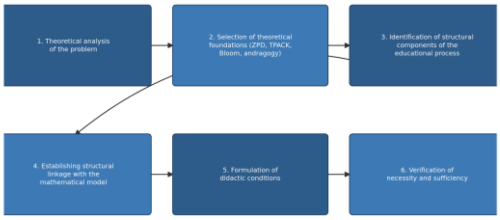

Figure 1. Stages of the research methodology.

Stage one located the problem: AI-based prediction in exam preparation is technically mature and didactically underspecified. The competence-based approach framing the whole analysis [4] treats readiness as the ability to apply knowledge, not merely hold it. Stage two selected four theories as lenses, each covering a distinct part of the process a predictive model touches: Vygotsky's zone of proximal development [9] for what content comes next; TPACK [10] for what a teacher needs to know to use the model's output; Bloom's taxonomy, in Anderson and Krathwohl's revision [11], for how diagnostic material should be built; and Knowles' andragogy [12] for how adult examinees — a large share of GRE and GMAT candidates — read feedback about their own progress. These four do not simply stack: three reinforce one another, and one sits in real tension with the rest, shown in Figure 2.

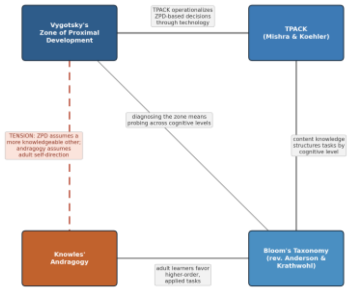

Figure 2. Relationships among the four theoretical foundations. Solid lines mark reinforcing connections; the dashed line marks a genuine tension between Vygotsky's child-development-based zone of proximal development and Knowles' assumption of adult self-direction, left unresolved here and revisited in Limitations.

Stage three named the structural components any such model touches: diagnostic, concerning what data enters it; content, concerning what changes about instruction; teacher-facing, concerning who interprets the output; and learner-facing, concerning who acts on it. Grounding “didactic conditions” itself in the literature [2; 3], stage four tied each component to a parameter of the model.

The mathematical model

The model treats readiness as a continuous-time stochastic process. Let X(t) denote examination-relevant competence at time t, governed by a generalization of the classical Ornstein–Uhlenbeck equation [13] that lets the long-run target vary as preparation proceeds:

$$dX(t) = \theta\,[\mu(t) - X(t)]\,dt + \sigma\,dW(t) \qquad (1)$$

Here μ(t) is the target for the current stage, itself potentially shifting as the curriculum advances; θ sets how fast pedagogical influence pulls the learner toward that target; σ is volatility from individual and situational factors; W(t) is a standard Wiener process. Within a stage, θ and σ are held locally constant, a simplification addressed in Limitations. The classical process assumes a fixed μ; letting it vary is what makes the model fit a curriculum that itself changes, hence a generalization of the 1930 original rather than the process in its original form.

Two properties matter here. First, mean reversion: absent new information, the expected path of X(t) moves toward μ(t) at rate θ, which is what makes the model a forecast rather than a random walk. Second, the conditional variance is not fixed; it evolves as

$$\mathrm{Var}\,[X(t) \mid X(0)] = \frac{\sigma^2}{2\theta}\left(1 - e^{-2\theta t}\right) \qquad (2)$$

converging to $\sigma^2/(2\theta)$ as t grows. That convergence later grounds the fourth condition. Figure 3 shows both properties for illustrative parameters, chosen for legibility rather than fitted to data.

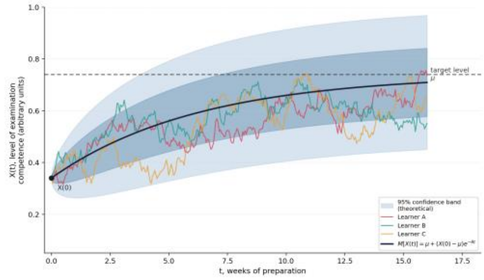

Figure 3. Illustrative dynamics of X(t) for three notional learners under θ = 0.16, μ = 0.74, σ = 0.075, X(0) = 0.34 (values chosen for demonstration, not an empirical result). The dark line is the theoretical mean; the shaded band, whose width converges to $\sigma^2/(2\theta)$, is the confidence corridor.

For computer-adaptive exams — GRE and GMAT among them — the need for regular observation lines up with computerized adaptive testing itself, where machine learning already refines an ability estimate as items are presented [14]. That alignment is part of why the diagnostic condition below counts as more than generic good practice.

Stage five turned this correspondence into the four conditions reported next. Stage six tested the result for necessity and sufficiency: what would break without each condition, and whether four conditions cover all four components without gap or overlap.

Result and Discussion. Four didactic conditions emerged, each necessary and, together, sufficient to cover the components named in Materials and Methods.

Continuity of diagnostic monitoring

The first condition is continuous, systematic monitoring that feeds the model. An initial assessment sets X(0), the learner's actual starting level; later observations build the trajectory X(t) that anchors both the forecast and the zone of proximal development.

Diffusion-type models like this one need regular, comparable observations to estimate parameters and produce a trustworthy forecast. Break that regularity and estimates drift — a real threat to the model, not a minor inconvenience. Pedagogically this is simply systematic, sequential instruction read through formative assessment theory [15]: short diagnostics built into teaching, spanning Bloom's levels from recall to evaluation, regular enough for the model and rich enough to reflect a genuinely multidimensional skill.

In practice this means a fixed schedule of checkpoints, one scoring scale across them, and automated collection so teacher time stays manageable.

Individualization of content and pace

The second condition individualizes content and pace from the model's forecasts, in the logic of the zone of proximal development [9]. The forecast trajectory and the gap to $\mu(t)$ locate that zone for a given learner: tasks beyond what is mastered but reachable with support. Miss that band, in either direction, and the developmental payoff drops, showing up as higher forecast variance.

Implementing this condition calls for modular content that can be reassembled as new data arrives, and support that scales up or down with the learner's own trajectory rather than a fixed pace.

Methodological-technological readiness of the teacher

The third condition asks the teacher to hold integrated readiness to interpret and act on the model's output, in the sense TPACK specifies [10] — and here the author's earlier work on interpretable diagnostics applies directly [7]. A statistically sound forecast becomes didactically useful only once a teacher turns its probabilities into a decision about content, pace, or classroom organization. Without that competence, a technically sound model meets an unsound practice, the familiar 'last mile' problem.

In practice this means a dedicated module in teacher training for translating statistics into decisions, plus guidance linking typical forecast patterns to classroom actions.

Reflexive-regulatory competence of the learner

The fourth condition builds the learner's own skill at working with the model's feedback. Many GRE and GMAT candidates are adults, and Knowles' andragogy [12] correctly predicts they want to plan their own study and see the point of what they are asked to do. Without this skill, forecast information gets absorbed passively, and whatever self-monitoring the process might have built fails to transfer forward.

Building this condition into instruction means a stage where learners review their own results, tie the forecast to a study plan, and complete reflective tasks aimed at setting the next goal.

Table 1 and Figure 4 summarize how the four conditions map to theory and to model parameters.

Table 1. The system of didactic conditions for applying dynamic AI models

#	Didactic Condition	Theoretical Basis	Model Parameter

1	Continuity of diagnostic monitoring	Systematicity principle; Bloom's taxonomy	X(0), θ, μ, σ — parameter estimation
2	Individualization of content and pace	Zone of proximal development (Vygotsky)	μ(t) — dynamic individualization
3	Teacher's methodological-technological readiness	TPACK model	Interpretation of θ, σ
4	Learner's reflexive-regulatory competence	Andragogy (Knowles)	$Var[X(t)] \to \sigma^2/(2\theta)$

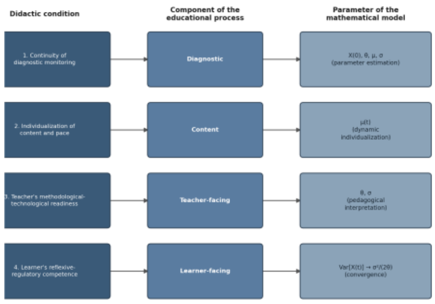

Figure 4. Structural-functional scheme linking each didactic condition, the corresponding component of the educational process, and the relevant parameter of the mathematical model.

Necessity and sufficiency follow from matching four independent components: diagnostic, content, teacher, learner. Drop the first and the model loses reliable input; drop the second and forecasts never individualize content; drop the third and output never gets interpreted; drop the fourth and any developmental gain disappears once the teacher steps back. A fifth condition would correspond to no new component, so it would be redundant.

This system tracks the model's own mathematics directly, which is what makes it one argument rather than four separate claims stitched together. θ, μ, and σ can only be estimated correctly if the first condition holds. Treating μ(t) as individualized and dynamic is what the second condition means mathematically. Using θ and σ to inform real decisions needs the third. The fourth ties to the model's own behavior: sustained support pushes the conditional variance in equation (2) toward its stationary value — falling uncertainty as the learner gains practice with feedback, visible in Figure 3 as the narrowing band. Holding that effect once the teacher steps back is what the fourth condition asks.

Each condition carries its own psychological-pedagogical justification and an objective mathematical one. Together they read as a single didactic-mathematical foundation, grounded in the technology's own mathematics rather than loosely associated best practice.

Limitations

Four limitations bound these claims. The conditions were reached deductively, from theory and structural correspondence, not from data; independent expert validation is a task for later.

The argument does not split conditions by learner age: SAT and ACT candidates are mostly adolescents, GRE and GMAT mostly adults, and andragogy [12] implies different degrees of external regulation for the fourth condition — the practical side of the tension in Figure 2, left unresolved here.

The motivational side of receiving a forecast also sits outside this paper's scope: a low-probability forecast could regulate behavior, as assumed here, or discourage a learner instead, and sorting that out belongs to educational psychology rather than didactics.

Equation (1) sets no bound on $X(t)$, though real score scales are bounded, an acceptable simplification for didactic rather than psychometric analysis, but a real limitation nonetheless.

One more point follows from Methods: holding θ and σ locally constant within a stage makes the model piecewise, and where stages break is a design choice this paper leaves open. None of the four conditions depends on resolving it, but a continuous-time version of the model eventually will.

Conclusion. Four conclusions follow. Didactic conditions, applied to dynamic AI models, name a specific set of content, procedural, and organizational factors whose presence decides whether the technology teaches anything at all. Four interdependent conditions have been justified: continuous monitoring, individualized pace, teacher readiness, and learner self-regulation. Each sits in an objective structural relationship with a model parameter (θ, μ, σ), giving the system coherence and keeping it consistent with the author's earlier mathematical work. The analysis yields a testable hypothesis: systematic implementation of these conditions improves preparation outcomes, relative to using the model without them, by a statistically detectable margin.

The next step is testing that hypothesis with control and experimental groups, alongside building diagnostic instruments for how fully each condition is implemented and the statistics needed to compare outcomes between groups.

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were collected. The demonstration in Figure 3 uses illustrative parameter values, not fitted or measured data.

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