Dual-process theory meets adaptive learning: A technical framework for educational AI

Kahneman's System 1/System 2 framework provides a powerful lens for designing adaptive learning systems that optimize both automaticity development and deep conceptual understanding. **The central insight: effective learning requires orchestrating transitions from effortful System 2 processing (deliberate, analytical) toward fluent System 1 processing (automatic, intuitive) while strategically re-engaging System 2 for transfer and metacognition.** This framework has generated specific algorithms, architectures, and measurement approaches now deployed in systems like Carnegie Learning, Duolingo, and modern intelligent tutoring systems.

The research synthesized here spans cognitive science foundations, learning engineering techniques, bias detection methods, and concrete technical implementations—providing both theoretical grounding and actionable system designs for educational technology developers.

Cognitive architecture foundations shape instructional design

Dual-process theory, refined by Evans and Stanovich (2013), distinguishes Type 1 processing (autonomous, working-memory-independent, pattern-based) from Type 2 processing (working-memory-dependent, rule-based, requiring cognitive decoupling). PubMed In learning contexts, **novices predominantly rely on Type 2 processing** when encountering new material, while **experts shift toward Type 1 for familiar patterns**, reserving System 2 for novel problems.

John Sweller's Cognitive Load Theory integrates directly with this framework. PubMed Central Working memory holds roughly **2-3 novel elements** without chunking—a severe constraint that instructional design must respect. ERIC Three load types interact: intrinsic load (inherent difficulty), extraneous load (poor design), and germane load (productive schema construction). The Decision Lab As expertise develops, schemas stored in long-term memory reduce intrinsic load, enabling automatic processing. The practical implication: **reduce extraneous load to free working memory for the effortful processing that builds transferable schemas**.

The expertise development trajectory follows predictable stages. Fitts and Posner's three-stage model describes movement from cognitive (System 2 dominant) through associative to autonomous (System 1 dominant) phases. Ericsson's deliberate practice research adds a crucial paradox: while everyday skills benefit from rapid automatization, **expert performers actively counteract automaticity** to maintain conscious control and continue improving. This suggests adaptive systems need different modes for fluency building versus expertise development.

Evidence-based techniques for developing System 1 automaticity

Four well-validated techniques drive automaticity development, each with specific implementation requirements for adaptive systems:

Spaced repetition leverages memory's exponential decay curve (Ebbinghaus, 1885) through expanding intervals. (PubMed Central) The Leicester study (2020) found effect sizes of **d = 0.54**, with spaced repetition users achieving 70% adjusted exam scores versus 61% for non-users. (ERIC) Neurobiologically, spacing allows hippocampal-independent memory consolidation through molecular processes including kinase activation and spine remodeling. (PubMed Central)

Interleaving mixes different skills within practice sessions rather than blocking. Rohrer and Taylor (2007) demonstrated **63% versus 20% correct on delayed tests** for interleaved versus blocked math practice. The mechanism: interleaving forces discrimination between similar concepts and requires renewed retrieval for each item. However, complete novices may benefit from initial blocking before transitioning to interleaving—hybrid approaches show strongest results for low-achieving learners.

Retrieval practice (the testing effect) remains one of psychology's most robust findings. Roediger and Karpicke (2006) showed that students who studied once then took three tests outperformed those who studied four times on delayed assessments. (ucla) The mechanism involves strengthening memory storage through retrieval effort. Even unsuccessful retrieval attempts followed by feedback enhance learning, suggesting systems should prompt retrieval at the edge of forgetting—where difficulty is "desirable."

Measuring automaticity requires multiple indicators. Response time reduction follows a power law with practice, stabilizing at asymptotic levels indicating automaticity. Stroop-like interference paradigms remain the gold standard: automatic processes cannot be "turned off" and thus interfere with controlled tasks. Dual-task methodologies assess whether skill execution degrades concurrent secondary task performance—automatic processes require minimal cognitive resources.

Metric	Interpretation	System Implementation
Response time trend	Decreasing RT indicates developing automaticity	Track rolling averages; trigger mastery assessment when asymptotic
RT variability	Lower variability signals expertise	Flag high-variance responses for targeted review
Stroop interference	Greater interference = stronger automaticity	Embed interference assessments for fluency validation
Dual-task cost	Lower cost = more automatic processing	Optional: secondary task probes during practice

Engaging System 2 for transfer and deep understanding

Automaticity alone produces brittle knowledge that fails to transfer. Strategic System 2 engagement develops flexible, generalizable understanding through four key mechanisms:

Metacognitive scaffolding based on Zimmerman's self-regulated learning framework guides learners through forethought (planning), performance (monitoring), and reflection phases. Meta-analysis by Guo (2022) found metacognitive prompts produced **g = 0.50 for SRL activities** and **g = 0.40 for learning outcomes**. Wiley Online Library Critical moderators include feedback presence, prompt specificity, and adaptability to individual learners. Task-specific, individually-adaptive prompts with feedback show the strongest effects. Wiley Online Library

Desirable difficulties (Bjork and Bjork, 2011) distinguish conditions that optimize immediate performance from those that optimize long-term learning. Spacing, interleaving, and generation all slow apparent learning while enhancing retention and transfer. ucla The critical caveat: difficulties are only "desirable" when learners have sufficient background knowledge to respond successfully and the difficulty triggers encoding processes that support learning.

Productive failure (Kapur) inverts traditional instruction by having students attempt problems before receiving instruction. Meta-analysis of **166 comparisons with 12,000+ participants** found productive failure students significantly outperformed direct instruction with **Cohen's d = 0.36** overall and **d = 0.58** for high-fidelity implementations—roughly three times the effect of one year with an effective teacher. boldscience The mechanism: struggle activates prior knowledge, draws attention to critical features, and prepares learners to benefit from subsequent instruction. boldscience

Self-explanation effects (Chi et al., 1989) show that students who generate explanations while studying achieve superior problem-solving outcomes with effect sizes of **d = 0.55-0.61**. Self-explanation prompts following worked examples are particularly effective, though time demands (often 2× longer) and cognitive load constraints must be managed.

Transfer from training to novel contexts remains challenging. Takinglearningseriously Near transfer (similar contexts) occurs reliably; far transfer requires deep initial learning, abstraction of underlying principles, and recognition of applicability. ScienceDirect Variable practice with multiple contexts, analogical reasoning, and explicit articulation of conditions of applicability all support transfer— Takinglearningseriously though effects remain modest compared to near-transfer gains.

Detecting and correcting cognitive biases in learning

Learner cognitive biases systematically undermine effective learning and self-assessment. Adaptive systems can detect bias indicators and deploy targeted interventions:

The Dunning-Kruger effect presents a fundamental challenge: low-performing students placed themselves at the **62nd percentile when actual performance was at the 12th percentile**. The mechanism involves a "dual burden"—lacking skill AND lacking metacognitive awareness to recognize the deficiency. High performers conversely underestimate relative standing.

Fluency illusions (Koriat and Bjork, 2005) cause students to mistake recognition familiarity for genuine recall ability. When information feels easy to process—through fluent instruction or smooth delivery—learners systematically overestimate their learning despite no improvement in actual test performance. This explains why desirable difficulties feel worse but work better. ucla

Confirmation bias drives selective engagement with materials that reinforce existing understanding, while **availability heuristic** causes overestimation of concepts that are memorable or recently encountered. In digital learning environments, algorithmic content selection can amplify these biases through filter bubbles.

Detection approaches leverage behavioral pattern analysis and machine learning:

Detection Method	Target Bias	Technical Approach
Calibration discrepancy analysis	Overconfidence	Compare confidence ratings to accuracy; track systematic patterns
Browsing pattern analysis	Confirmation bias	Monitor selective engagement with confirming vs. disconfirming content
Time-series behavioral analysis	Multiple	Establish baselines; detect deviations using UEBA principles
NLP analysis of responses	Framing, epistemological bias	BERT-based classifiers; feature extraction for hedge detection
LLM-based structured prompting	Circular reasoning, confirmation	99%+ detection rates with advanced prompt engineering

Debiasing interventions show meaningful but variable effectiveness. Morewedge et al. (2015) found game-based training produced **immediate effects ≥ 31.94%** reduction in bias with **2-month retention ≥ 23.57%**. Games with personalized feedback outperformed videos. Consider-the-opposite interventions reduced confirmatory hypothesis testing by **29%** in field studies. However, simply warning about bias or instructing objectivity does NOT reduce bias—structured intervention with feedback and practice is required.

Effective bias correction requires:

- Immediate feedback as "cognitive mirrors" revealing calibration gaps Didask
- Consider-the-opposite prompts at decision points (limited to 2 reasons)
- Retrieval practice to dispel fluency illusions
- Guided reflection with specific focus on alternative outcomes

Intelligent tutoring system architectures

The classic ITS architecture comprises four interacting models: **domain model** (expert knowledge, production rules), **student model** (knowledge state tracking), **tutoring model** (pedagogical strategy selection), and **user interface model** (interaction design). Wikipedia Modern implementations extend this with machine learning components for knowledge tracing and adaptive content selection.

Carnegie Learning's cognitive tutors, grounded in ACT-R theory, exemplify production-rule-based tutoring. Knowledge is represented as if-then production rules; the system continuously updates probability estimates of rule mastery, drilling until reaching a **95% mastery threshold**. Documented outcomes include ~100% higher scores on problem-solving tests and ~15% higher standardized assessment scores, with programming students completing problems in 1/3 the time while scoring 25% higher.

VanLehn's **inner/outer loop framework** (2006) distinguishes task-level adaptation (outer loop: selecting problems based on student model) from step-level feedback (inner loop: immediate guidance within tasks). The inner loop enables model tracing—matching each student action against the expert model to provide targeted feedback. This dual-loop architecture maps directly to System 1/System 2 training modes: inner loop immediate feedback supports automaticity while outer loop strategic sequencing enables conceptual development.

Knowledge tracing algorithms estimate learner knowledge state from interaction data:

Bayesian Knowledge Tracing (BKT) uses a two-state hidden Markov model with four parameters: $P(L_0)$ initial knowledge probability, P(T) learning transition probability, P(G) guess probability, and P(S) slip probability. Wikipedia After each interaction, the system updates $P(L_n|\text{evidence})$ using Bayesian inference: Physicsfront

$$P(L_n|\text{correct}) = P(L_n)(1-P(S)) / [P(L_n)(1-P(S)) + (1-P(L_n))P(G)]$$
$$P(L_{n+1}) = P(L_n|\text{evidence}) + (1 - P(L_n|\text{evidence})) \times P(T)$$

Mastery is declared when $P(L_n)$ reaches threshold (typically 0.95; research suggests 0.98 yields additional benefits). BKT achieves typical AUC of 0.73-0.83 on benchmark datasets.

Deep Knowledge Tracing (Piech et al., 2015) uses LSTM networks to model temporal dynamics without explicit knowledge engineering. Input sequences encode (exercise_id, correctness) pairs; output provides probability vectors for all knowledge components. PubMed Central DKT achieved **25% AUC improvement** over BKT on the ASSISTments dataset (0.86 vs 0.69), though interpretability suffers. Variants include DKVMN (memory-augmented networks), PubMed Central SAKT (self-attention, Educationaldatamining 46× faster training), and AKT (context-aware attention with IRT-based embeddings).

Real-time adaptation employs multiple algorithmic approaches:

Multi-armed bandit algorithms address exploration-exploitation tradeoffs in content selection. Thompson Sampling (Bayesian approach sampling from posterior distributions) and LinUCB (contextual bandit with linear reward model) enable personalization with limited prior data. Duolingo uses bandits for lesson selection combined with forgetting curve modeling.

Reinforcement learning optimizes tutoring policies for long-term learning outcomes. The STEP framework uses PPO (Proximal Policy Optimization) with knowledge tracing for instructional sequencing. RL tutors consistently show **greatest benefits for students with lower initial pretest scores**, suggesting adaptive AI can support those most in need.

Concrete algorithm implementations and tools

Spaced repetition algorithms

SM-2 (SuperMemo, 1987) remains widely used. The easiness factor EF (initial 2.5, minimum 1.3) updates based on response quality q (0-5): Wikipedia

```
EF' = EF + (0.1 - (5-q) × (0.08 + (5-q) × 0.02))
```

Intervals: I(1)=1 day, I(2)=6 days, I(n)=I(n-1)×EF for n>2. Incorrect responses reset to I=1. Wikipedia

FSRS (Free Spaced Repetition Scheduler, v6) models difficulty, stability, and retrievability GitHub with 21 trainable parameters. GitHub Retrievability follows:

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R = (1 + t/(9×S))^(-1)
```

Stability updates depend on difficulty, prior stability, retrievability, and grade. FSRS outperforms SM-2 through personalized parameter optimization on user data. RemNote

Half-Life Regression (Duolingo) predicts memory half-life h—time until recall probability drops to 50%:

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p = 2^(-Δ/h)    where h = 2^(θ·x)
```

Feature vectors include right/wrong history, lag time, and lexeme-specific weights. HLR achieves ~50% lower error than Leitner systems.

Open-source implementations

Tool	Type	URL	Key Features
pyKT	Knowledge tracing	github.com/pykt-team/pykt-toolkit	10+ models (DKT, SAKT, AKT); 7+ datasets
pyBKT	BKT	github.com/CAHLR/pyBKT	Standard + variants; Python/C++

Tool	Type	URL	Key Features
fsrs	Spaced repetition	pypi.org/project/fsrs/	FSRS v6; cross-platform
OATutor	ITS platform	github.com/CAHLR/OATutor	BKT-based; React frontend; A/B testing
GIFT	ITS authoring	gifttutoring.org	Domain-independent; experiment platform

Benchmark datasets

Dataset	Interactions	Students	Source
ASSISTments 2009	346,860	4,217	assistmentsdata
ASSISTments 2012	6,123,270	46,674	assistmentsdata
Duolingo HLR	13M pairs	—	github.com/duolingo
FSRS-Anki-20k	—	20,000	open-spaced-repetition

Metrics framework

Learning gains: Normalized gain g = (post-pre)/(max-pre); g<0.3 low, 0.3-0.7 medium, >0.7 high. Cohen's d for effect sizes (0.2 small, 0.5 medium, 0.8 large; Hattie's average benchmark = 0.40).

Mastery estimation: BKT-based P(mastery) ≥ 0.95 threshold; N-consecutive-correct heuristics (typically 3-5).

Fluency metrics: Response time mean/variance/trend; accuracy moving averages; automaticity index (speed × accuracy).

Retention modeling: Ebbinghaus curve R(t) = e^(-t/S) for forgetting estimation; SuperMemo stability S from FSRS for personalized scheduling.

Population-specific design adaptations

ADHD learners

ADHD's executive function profile—working memory constraints, attention regulation difficulties, reduced inhibition—requires specific adaptations. Evidence-based approaches include:

- **Adaptive chunking**: Micro-sessions (5-15 minutes) matching attention span with built-in breaks
- **Real-time engagement monitoring**: Detect disengagement through interaction patterns; deploy intervention prompts

- **Gamification**: Progress visualization, achievements, rewards to sustain motivation
- **Movement integration**: Kinesthetic elements, exergaming approaches combining cognitive training with physical activity
- **Structured environments**: Predictable interfaces, reduced visual clutter, clear organization

Programming education

Programming carries inherently high intrinsic cognitive load due to element interactivity. Expert-novice research reveals experts use semantic chunking and top-down comprehension while novices process surface-level syntax. Effective approaches:

- **Worked examples with fading**: Reduce problem-solving load; CORT-style part-completion
- **Subgoal labels**: Break problems into labeled components to support transfer
- **Parsons problems**: Code arrangement tasks reducing cognitive load while building comprehension
- **Progressive code completion**: Start nearly-complete, gradually increase missing portions
- **Semantic feedback beyond syntax**: Address conceptual misconceptions, not just compilation errors

Adult learners

Knowles' andragogy principles emphasize that adults need to understand WHY they're learning (relevance), are self-directed (require autonomy), bring rich experience (connect to prior knowledge), prefer problem-centered learning (case studies, scenarios), and respond to internal motivation (career advancement, personal growth).

Design implications: goal transparency upfront, learner control over pace/sequence, experience integration through reflection prompts, just-in-time microlearning for time-constrained schedules, and explicit career/job task connections.

Accessibility

Universal Design for Learning (CAST) provides three principles: multiple means of **engagement** (recruiting interest, sustaining effort), **representation** (perception options, comprehension support), and **action/expression** (physical action, executive function support). WCAG 2.2 Level AA compliance is the regulatory baseline, requiring perceivable, operable, understandable, and robust interfaces.

Neurodiversity-affirming design shifts from deficit-based to strengths-based approaches, treating neurodivergent conditions as natural human variation. Key features: predictable navigation, clear language, error prevention/recovery, memory aids, and customizable sensory input.

Synthesis: An integrated dual-process architecture

The research synthesized here suggests an adaptive learning architecture organized around dual-process optimization:

System 1 training mode (automaticity/fluency):

- High-frequency practice on similar problem types with immediate inner-loop feedback
- Spaced repetition scheduling (FSRS or HLR) for long-term retention
- N-consecutive-correct mastery gates (typically 3-5, or BKT $P(L) \geq 0.95$)
- Response time and fluency metric tracking
- Minimal elaboration; efficiency-focused

System 2 training mode (understanding/transfer):

- Varied problem types requiring analysis with delayed outer-loop feedback
- Productive failure sequences (problem-solving before instruction) for key concepts boldscience
- Self-explanation prompts, especially following worked examples
- Metacognitive scaffolds (planning, monitoring, reflection) Springer
- Consider-the-opposite prompts for bias correction

Adaptive switching triggers:

- Knowledge tracing state estimates (mastery threshold crossings)
- Response time patterns (fast=System 1 ready; slow=System 2 engaged)
- Error pattern analysis (fluency breakdown indicates need for System 2 re-engagement)
- Confidence calibration (overconfidence triggers bias intervention)

The architecture implements VanLehn's inner/outer loop structure, with inner loops providing step-level feedback for automaticity and outer loops orchestrating task selection for conceptual development. Multi-armed bandits (Thompson Sampling, LinUCB) handle content selection with limited prior data; reinforcement learning optimizes policies for students requiring additional support.

This integrated framework—grounded in cognitive science, operationalized through specific algorithms, and validated on substantial research evidence—provides a principled foundation for educational technology that genuinely optimizes human learning.