COGNITIVE ARCHITECTURES IN ADAPTIVE LEARNING: SYNTHESIZING COGNITIVE LOAD THEORY, MENTAL MODELS, AND DUAL-PROCESS FRAMEWORKS FOR NEXT-GENERATION EDUCATIONAL SYSTEMS

1. Introduction: The Transition from Static to Cognitive-Adaptive Architectures

The landscape of educational technology is currently undergoing a fundamental phase shift, transitioning from static content delivery systems to dynamic, cognitive-adaptive environments. Historically, "adaptive learning" was often a misnomer for simple branching logic—conditional pathways triggered by binary success or failure on assessment items. However, the convergence of advanced cognitive science, granular educational data mining, and machine learning has rendered these primitive models obsolete. The current frontier of research focuses on architectures that model the learner not merely as a recipient of information, but as a complex cognitive agent subject to specific constraints (working memory), operating with distinct processing modes (System 1 vs. System 2), and organizing information into structural schemas (mental models).[1]

This report investigates the integration of three foundational cognitive frameworks—Cognitive Load Theory (CLT), Mental Model Theory, and Dual-Process Theory—into the engineering of adaptive learning systems. The premise of this synthesis is that an effective educational system must act as an external regulator of the learner's cognitive state. It must continuously estimate the load on working memory to prevent catabolic failure (overload) while maintaining the anabolic stress required for schema construction (germane load). It must distinguish between the need for fluency (System 1) and the need for deep conceptual restructuring (System 2), adjusting its pedagogical strategy accordingly. Furthermore, it must possess the metacognitive awareness to detect and correct the learner's own cognitive biases, such as overconfidence and confirmation bias, which often act as invisible barriers to expertise acquisition.

By examining the mechanisms of the **Expertise Reversal Effect**, the algorithms behind **real-time load estimation**, and the methodologies for **bias detection**, we can delineate the blueprint for a "Cognitive Operating System" for education—one that adapts not just to *what* the student knows, but to *how* the student thinks.

2. Cognitive Load Theory: The Thermodynamic Limit of Instructional Design

Cognitive Load Theory (CLT), originating from the work of John Sweller, provides the foundational physics for adaptive learning systems. It posits that human working memory is severely limited in both capacity and duration, acting as a bottleneck for information processing. Instructional design, therefore, becomes an exercise in resource management, aiming to optimize the allocation of these finite cognitive resources.[2] In the context of adaptive systems, CLT is not merely a design heuristic but a quantifiable metric that drives real-time decision-making engines.

2.1 The Triarchic Model and Algorithmic Regulation

Adaptive systems must differentiate between three distinct types of cognitive load, as each requires a different algorithmic response.

Intrinsic Cognitive Load represents the inherent complexity of the learning material itself, defined by its "element interactivity"—the number of interacting information elements that must be processed simultaneously. For instance, learning a list of vocabulary words involves low element interactivity (each word can be learned in isolation), whereas solving an algebraic equation involves high element interactivity (the learner must simultaneously hold the variables, the operations, and the rules of transformation in working memory).[1] Adaptive systems regulate intrinsic load through segmentation and sequencing algorithms. By analyzing the dependency structure of knowledge components, systems can break high-complexity tasks into smaller, isolated sub-tasks, gradually increasing element interactivity only as the learner demonstrates the capacity to handle it. This aligns with Vygotsky's concept of the **Zone of Proximal Development (ZPD)**, where the system targets a success rate of 35–70% to maintain the learner in a state of "desirable difficulty".[1]

Extraneous Cognitive Load is the cognitive cost imposed by the instructional environment itself—poor interface design, split attention, or redundant information. In static media, this is a fixed design flaw. In adaptive systems, extraneous load is a dynamic variable that can be minimized through "stealth" interface adjustments. For example, the **Split-Attention Effect** occurs when learners must mentally integrate spatially separated information (e.g., a diagram and its caption). Adaptive interfaces can dynamically merge these sources based on the learner's gaze patterns or mouse hover behavior, physically integrating the text into the diagram to reduce the search cost.[1]

Germane Cognitive Load refers to the mental resources devoted to the acquisition and automation of schemas—the structural organization of knowledge in long-term memory. Unlike extraneous load, which must be minimized, germane load must be maximized. Adaptive systems encourage this through prompts that trigger **System 2** processing (discussed in Section 3), such as self-explanation or comparison tasks. The goal is to convert the free capacity created by reducing extraneous load into germane processing.[2]

2.2 The Expertise Reversal Effect: When Help Becomes Hindrance

One of the most critical and counter-intuitive phenomena in CLT is the **Expertise Reversal Effect**. This effect describes the inversion of instructional efficacy as a learner gains proficiency: techniques that are highly effective for novices (such as worked examples) become ineffective or even detrimental for experts.[4]

2.2.1 The Mechanism of Redundancy

For a novice, a worked example functions as a surrogate schema. Lacking the internal structure to organize the problem space, the novice relies on the step-by-step external guidance to reduce intrinsic load and facilitate understanding. However, as the learner acquires expertise, they develop internal schemas that guide their problem-solving. When an expert is forced to process a worked example, they encounter a conflict between their internal schema and the external information. The effort required to cross-reference the redundant external guidance with their efficient internal knowledge imposes an unnecessary cognitive tax—specifically, the **Redundancy Effect**.[4] This redundant processing consumes working memory resources that could otherwise be used for fluency or transfer, actually depressing performance compared to solving the problem independently.[2]

2.2.2 Algorithmic Solutions: Adaptive Fading

To mitigate the expertise reversal effect, adaptive systems employ **Adaptive Fading** algorithms. Instead of a fixed sequence of instruction (e.g., "Explanation → Example → Problem"), the system dynamically adjusts the level of scaffolding based on the learner's real-time performance and estimated expertise level.[5]

The implementation of adaptive fading typically follows a "completion problem" logic.

1. **Stage 1 (Novice):** The learner receives a fully worked-out example.
2. **Stage 2 (Intermediate):** The system presents a "faded" example where the final steps are omitted, requiring the learner to complete the solution.
3. **Stage 3 (Advanced):** The system fades earlier steps, requiring the learner to initiate the solution strategy but perhaps providing the final calculation.
4. **Stage 4 (Expert):** The scaffolding is entirely removed, and the learner solves the full problem independently.

Research demonstrates that adaptive fading based on **demonstrated understanding**—triggered by metrics such as rapid, correct responses or high-quality self-explanations—significantly outperforms fixed fading schedules.[5] For instance, the **Intelligent Adaptive Learning** engine used by platforms like DreamBox or MATHia tracks the strategy a student uses, not just the answer. If a student demonstrates a sophisticated, efficient strategy (indicating schema acquisition), the system accelerates the fading process. Conversely, if a student reverts to a brute-force method, the scaffolding is reinstated. This dynamic calibration ensures that the instructional support remains aligned with the learner's cognitive state, preventing the expertise reversal effect from stalling progress.[1]

2.3 Real-Time Cognitive Load Estimation: The Sensor Architecture

The theoretical application of CLT requires a reliable "thermometer" for cognitive load. Traditional methods relying on self-reporting (e.g., NASA-TLX surveys) are disruptive and retrospective, breaking the flow of learning. Modern adaptive systems have moved toward **stealth assessment**, inferring cognitive load in real-time from behavioral and physiological signals.[1]

2.3.1 Mouse Dynamics and Trajectory Analysis

Perhaps the most scalable method for cognitive load estimation is the analysis of mouse dynamics. Mouse tracking requires no special hardware, making it universally applicable in web-based learning. The premise is that the motor control system competes for resources with the cognitive system; therefore, changes in cognitive demand manifest in motor behavior.[10]

Feature engineering in this domain has identified several robust predictors:

- **Velocity and Acceleration Profiles:** High cognitive load is consistently associated with slower mean response times and lower peak velocities. The "thought" required to process high-load information slows the physical initiation of movement.[10]
- **Trajectory Deviation and Entropy:** The relationship between load and trajectory is complex. While intuitively one might expect "jittery" or erratic movements under load, some research suggests that higher cognitive load can actually lead to *less* trajectory deviation (straighter, more economical paths) but with significantly longer pauses. This phenomenon is attributed to the user inhibiting unnecessary motor action to conserve cognitive resources for the primary task.[10] Conversely, other models analyzing "mouse entropy" find that confusion or uncertainty (high extraneous load) leads to high-entropy, chaotic movement patterns as the user searches for information.[9]
- **Idle Time Analysis:** The duration and frequency of "micro-pauses" (where the mouse is stationary) are strong indicators of **System 2** activation. Long idle times during a problem-solving task typically signal deep processing or impasse, whereas continuous movement suggests System 1 automaticity.[11]

2.3.2 Eye-Tracking and Pupillometry

In environments equipped with webcams or specialized sensors, gaze data provides the highest temporal resolution for load estimation.

- **Task-Evoked Pupillary Response (TEPR):** The diameter of the pupil is a direct physiological correlate of locus coeruleus-norepinephrine activity, which tracks cognitive intensity. Pupil dilation reliably indicates increases in cognitive load, allowing systems to detect the precise moment a task becomes too difficult.[12]
- **Gaze Entropy and Fixation:** High cognitive load is often characterized by longer fixation durations (staring at a complex element to process it) and reduced saccadic range (tunnel vision). Conversely, high *extraneous* load (confusion) can lead to rapid, scattered saccades as the learner visually searches for connecting information.[12]

2.3.3 Keystroke Dynamics

For text-based inputs, keystroke dynamics provide a rich data stream. Metrics such as **flight time** (the latency between releasing one key and pressing the next) and **dwell time** (how long a key is depressed) vary significantly with cognitive state. Increased flight times and irregular typing rhythms (high arrhythmia) are strongly correlated with increased cognitive load, as the central executive pauses to plan the next segment of text production.[15]

2.3.4 Multimodal Fusion via Deep Learning

The most advanced systems do not rely on a single signal but employ **multimodal fusion**. By feeding mouse trajectories, keystroke patterns, and eye-tracking data into **Deep Neural Networks**—specifically **Long Short-Term Memory (LSTM)** networks or **Transformers**—adaptive systems can construct a robust "Cognitive Load Index." These models can handle the varying sampling rates of different sensors and capture long-term temporal dependencies, such as the gradual onset of fatigue or the sudden spike of frustration.[9] For example, an LSTM model might detect a pattern where a student's mouse velocity drops, pupil dilation spikes, and keystroke latency becomes erratic—a composite signature of cognitive overload that triggers an immediate intervention, such as providing a hint or simplifying the interface.[19]

3. Dual-Process Theory: Architectural Implications for Adaptive Systems

Dual-Process Theory, prominently articulated by Daniel Kahneman, divides human cognition into **System 1** (fast, automatic, intuitive, pattern-matching) and **System 2** (slow, deliberate, analytical, logical).[20] Adaptive learning systems must be architected to deliberately engage and develop both systems, but through fundamentally different pedagogical mechanisms.

3.1 System 1 Architecture: Developing Automaticity through Spaced Repetition

System 1 handles approximately 98% of daily cognitive tasks.[1] In an educational context, System 1 corresponds to "fluency" or "mastery"—the ability to recall facts, recognize patterns, or execute procedures without conscious effort. This automaticity is vital because it reduces the intrinsic load of foundational tasks (like reading or basic arithmetic), freeing up System 2 resources for higher-order problem solving.[21]

The primary mechanism for training System 1 is **Spaced Repetition**. By reviewing information at increasing intervals, learners consolidate memories, moving them from fragile working memory to robust long-term schemas.

3.1.1 The Evolution of Scheduling Algorithms: SM-2 to FSRS

For decades, the **SM-2 algorithm** (utilized by Anki) has been the standard for spaced repetition. SM-2 relies on a user-defined "Ease Factor" to determine intervals. However, it suffers from rigidity; it cannot effectively distinguish between the intrinsic difficulty of a card and the stability of the memory, often leading to "ease hell" where users are trapped in inefficient review loops.[1]

The new frontier is the **Free Spaced Repetition Scheduler (FSRS)**, a machine-learning-based algorithm that significantly outperforms heuristics like SM-2. FSRS is built on the **Three-Component Model of Memory**:

1. **Retrievability (R):** The probability that a learner can recall a specific item at a given moment. This decays over time according to the forgetting curve.
2. **Stability (S):** The durability of the memory, defined as the time required for Retrievability to drop from 100% to 90%.
3. **Difficulty (D):** The inherent complexity of the item, which determines how hard it is to increase Stability after a successful review.[24]

Table 1: Comparative Analysis of Spaced Repetition Algorithms

Metric	SM-2 (Standard)	FSRS (Machine Learning)
Model Basis	Heuristic multipliers based on "Ease Factor"	**DSR Model** (Difficulty, Stability, Retrievability)
Adaptability	Static rule-set; prone to rigid intervals	**Dynamic;** parameters optimized via gradient descent on user history
Efficiency	Baseline efficiency	**20-30% fewer reviews** for equivalent retention [1]
Retention Control	Indirect; via interval	**Direct;** user sets "Desired

	modifiers	Retention" (e.g., 0.9)
Performance	Benchmark standard	**99.6% superiority** in predictive accuracy benchmarks [1]
Delay Handling	Simplistic reset or slight boost	**Post-Lapse Stability;** accurately models memory after long breaks

By mathematically modeling the decay of Retrievability (R) as a function of Stability (S) and time (t), FSRS allows the system to identify the **Minimum Effective Dose (MED)** of practice. It schedules a review *exactly* when R hits the desired threshold (e.g., 90%), maximizing the memory strengthening effect of the retrieval attempt ("desirable difficulty") while minimizing the total volume of reviews.[1]

3.2 System 2 Architecture: Engaging Analysis through Interleaving

While System 1 thrives on repetition and consistency, System 2 requires novelty and contrast. The most effective strategy for engaging System 2 and fostering deep conceptual transfer is **Interleaved Practice**.

3.2.1 The Interleaving Effect

Interleaving involves mixing different types of problems or concepts within a single study session (e.g., ABCABCABC) rather than blocking them by type (AAABBBCCC).

- **The Illusion of Competence:** Blocked practice often leads to rapid performance gains during the session because the learner does not need to identify *which* strategy to use—they simply repeat the same strategy "A" for every problem in the "A" block. This relies on System 1 pattern matching.[26]
- **The Discriminative Contrast Hypothesis:** Interleaving forces the learner to actively discriminate between problem types (e.g., "Is this a permutation or a combination problem?") before solving them. This constant switching and decision-making engages System 2, leading to deeper encoding and better schema differentiation.[26]

3.2.2 Efficacy and Domain Differences

The superiority of interleaving for long-term retention and transfer is robustly supported by data.

- **Retention:** Studies show effect sizes ranging from **$d = 0.64$ to 1.34** in favor of interleaving for delayed tests.[1]
- **Domain Specificity:** The effect is particularly strong in mathematics, category learning (e.g., identifying painting styles or bird species), and medical diagnosis.[26] In one study

involving middle school math, interleaved groups scored **25% higher** on a test one day later and **76% higher** on a test one month later compared to blocked groups.[27]
- **Hybrid Approaches:** Because interleaving increases cognitive load (and error rates) during the initial acquisition phase, adaptive systems often employ a **hybrid schedule**. Novices are introduced to new concepts via short blocks (to lower intrinsic load and establish the basic schema), then rapidly transitioned to interleaved practice to enforce discrimination and retention (System 2 engagement).[1]

4. Mental Models and Knowledge Representation

To organize the curriculum effectively, adaptive systems must move beyond linear lists of skills and adopt a network-based approach that reflects the interconnected nature of human knowledge. This involves synthesizing **Mental Model Theory** with **Knowledge Graph** technology.

4.1 The Latticework of Mental Models

Charlie Munger's concept of a "latticework of mental models" suggests that a core set of 80-90 transferable concepts can explain the vast majority of real-world phenomena. Rather than teaching isolated facts, education should focus on installing these models.[1]

Key Models for Educational Systems:

- **First Principles Thinking:** Deconstructing complex problems into their most basic, foundational elements. Adaptive systems can teach this by requiring learners to identify the axioms or "atomic" units of a problem before attempting a solution.[1]
- **Inversion:** Solving problems by addressing the inverse (e.g., "How could I ensure failure?"). Systems can operationalize this by presenting "anti-patterns" or common misconceptions and asking students to debug them.[1]
- **Circle of Competence:** Helping learners calibrate the boundary between what they know and what they assume. This ties directly to bias detection (discussed in Section 5).[1]
- **Second-Order Thinking:** Evaluating consequences. Simulations and game-based environments are ideal for teaching this model, as they allow learners to experience the downstream effects of their decisions in a compressed timeframe.[1]

4.2 Knowledge Graphs: The Technical Implementation

The structural backbone that enables this "latticework" approach is the **Knowledge Graph (KG)**. In an adaptive system, the curriculum is represented as a directed graph $G = (V, E)$.

- **Vertices (V):** Represent individual concepts (nodes), such as "photosynthesis," "differential calculus," or "supply and demand."
- **Edges (E):** Represent relationships. The most critical are **prerequisite** relations (Node A is required to learn Node B) and **semantic** relations (Node A is related to Node B).[30]

4.2.1 Automated Graph Construction

Manually building these graphs is labor-intensive. Modern systems utilize **Natural Language Processing (NLP)** to automate the process from unstructured text (textbooks, video transcripts).[1]

1. **Concept Extraction:** Using BERT-based models and Named Entity Recognition (NER) to identify key educational concepts. Systems like **KnowEdu** achieve F1 scores >0.70 in this task.[1]
2. **Prerequisite Identification:** Algorithms analyze the text to determine dependency directions. If Concept A frequently appears before Concept B, and Concept B relies on terms defined in Concept A, a prerequisite edge is drawn. KnowEdu achieves an **AUC of 0.95** in identifying these relations.[1]
3. **Dynamic Weighting:** The "strength" or "difficulty" of the edge (the transition cost between concepts) is not static. It is dynamically updated based on aggregate learner data. If many students fail when moving from A to B, the system increases the weight of that edge, perhaps triggering the insertion of intermediate bridging content.[32]

4.2.2 Graph Traversal and the ZPD

The KG allows the system to algorithmically determine the **Zone of Proximal Development (ZPD)**. The learner's current knowledge state is a set of "marked" nodes on the graph. The "outer fringe"—the set of unmastered nodes that are directly connected to mastered nodes—represents the ZPD. The system uses algorithms (like Multi-Armed Bandits) to select the optimal next node from this fringe, ensuring the content is neither too easy (already mastered) nor too hard (lacking prerequisites).[1]

5. Bias Detection and Metacognitive Calibration

A truly adaptive system does not just correct content errors; it corrects cognitive errors. **Cognitive biases**, particularly overconfidence and confirmation bias, act as "meta-errors" that corrupt the learning process itself. Detecting and mitigating these biases is the new frontier of educational data mining.[1]

5.1 The Calibration Problem: Detecting Overconfidence

Overconfidence Bias (or the Dunning-Kruger effect) occurs when a learner's subjective confidence exceeds their objective accuracy. This is a critical failure mode because overconfident learners stop studying prematurely, believing they have achieved mastery.[34]

5.1.1 Detection Metrics

Adaptive systems detect this "calibration gap" by integrating metacognitive prompts.

- **Confidence Ratings:** Learners are asked to rate their confidence (e.g., 0-100% or Likert

scale) before or after answering a question.
- **Calibration Curves:** The system plots subjective confidence against objective accuracy. A perfectly calibrated learner aligns with the diagonal ($y=x$). Points below the diagonal represent overconfidence; points above represent underconfidence.[35]
- **Bias Scores:** A quantitative metric, often calculated as the signed difference between mean confidence and mean accuracy ($\text{Bias} = \text{Conf} - \text{Acc}$). High positive bias scores trigger intervention.[36]

5.1.2 Debiasing Interventions

Once overconfidence is detected, the system can deploy targeted interventions:

- **Visual Feedback:** Showing the learner their own calibration curve to objectively demonstrate the gap between their perception and reality.[35]
- **Forced Reflection:** Implementing a "consider the opposite" strategy. Before accepting a high-confidence answer, the system asks, "What is one reason this answer might be wrong?" This forces **System 2** activation and breaks the System 1 "feeling of knowing".[37]
- **Adaptive Disfluency:** For learners who answer too quickly with high confidence (a sign of shallow System 1 processing), the system can artificially introduce disfluency—such as delaying the "submit" button or changing the font—to slow them down and force analytical processing.[38]

5.2 The Filter Bubble: Detecting Confirmation Bias

In inquiry-based learning or "Search as Learning" (SAL) tasks, **Confirmation Bias** manifests as the tendency to seek out information that supports a prior belief while ignoring contradictory evidence.[39]

5.2.1 Behavioral Signatures in Logs

Analysis of search logs reveals distinct patterns for biased learners:

- **Query Formulation:** Biased learners issue longer, more specific queries designed to retrieve confirming results (e.g., "why is nuclear power bad") rather than neutral queries.[39]
- **Selective Exposure:** They click on lower-ranked results if those results align with their bias, while skipping higher-ranked contradictory results.
- **Dwell Time Variance:** Biased learners spend significantly *less* time on Search Engine Results Pages (SERPs) and on individual documents. They are "hunting" for confirmation rather than "gathering" knowledge. This rapid, shallow engagement is a detectable signal in the clickstream data.[39]

5.2.2 Algorithmic Mitigation

To counter this, systems can employ:

- **Bias Visualization Maps:** A dashboard that visually represents the "ideological spectrum" of the content the user has consumed, highlighting the "blind spots" they have ignored.[41]
- **Counter-Recommendation:** Algorithms that detect a "confirmation spiral" can deliberately inject high-quality, contradictory sources into the user's feed, boosting their visibility to ensure exposure to diverse viewpoints.[40]

6. Algorithmic Foundations: The Machine Learning Stack

The theoretical frameworks discussed above are operationalized through specific machine learning architectures.

Knowledge Tracing:

- **Bayesian Knowledge Tracing (BKT):** Uses Hidden Markov Models (HMM) to infer the latent "knowledge state" (learned/unlearned) of a skill based on binary performance data. While interpretable, it treats skills as independent.[6]
- **Deep Knowledge Tracing (DKT):** Uses Recurrent Neural Networks (RNNs) or LSTMs to capture complex, non-linear dependencies and temporal patterns in learning, significantly outperforming BKT in predictive accuracy.[1]
- **Transformer Models (SAKT, NTKT):** The cutting edge. These models use self-attention mechanisms to weigh the relevance of past interactions, allowing the system to understand long-range dependencies and sparse connections between concepts. NTKT has achieved F1 scores up to 90%.[1]

Reinforcement Learning (RL):

- **Multi-Armed Bandits (MAB):** Used for content selection. The system balances "exploitation" (showing content known to work) with "exploration" (trying new content). Algorithms like **Thompson Sampling** allow the system to converge on the optimal learning path for each student.[1]
- **Policy Optimization:** RL agents can learn optimal "scaffolding policies"—determining exactly when to give a hint, a worked example, or a problem to maximize long-term learning gains.[43]

7. Conclusion

The integration of Cognitive Load Theory, Mental Models, and Dual-Process Theory into adaptive learning systems represents a maturation of the field. We are moving away from systems that merely digitized the textbook toward systems that digitize the *tutor*.

By accurately measuring cognitive load through mouse dynamics and pupillometry, systems can keep learners in the optimal zone of engagement. By distinguishing between System 1 and System 2, architectures can balance the need for rapid automaticity (via FSRS) with deep conceptual inquiry (via interleaving). By detecting biases like overconfidence and confirmation bias, these tools can correct the metacognitive errors that often go unnoticed in traditional classrooms.

The future of educational technology lies in this "Cognitive Symbiosis"—a partnership where the machine handles the logistics of memory and scheduling, freeing the human mind to focus on the difficult, messy, and uniquely human work of building deep understanding.

Table 2: Synthesis of Frameworks and Technical Implementations

Cognitive Framework	**Educational Goal**	**Technical Implementation**
Cognitive Load Theory	Regulate difficulty; Minimize distraction.	**Mouse/Keystroke Dynamics:** Real-time load estimation. **Adaptive Fading:** RL-driven removal of scaffolding.
Dual-Process Theory	Balance Fluency (Sys 1) & Analysis (Sys 2).	**Sys 1:** FSRS (ML-based Spaced Repetition). **Sys 2:** Interleaved Practice & Discriminative Contrast.
Mental Models	Interconnected, transferable knowledge.	**Knowledge Graphs:** NLP-constructed concept maps ($G=V,E$). **ZPD Traversal:** Algorithms to identify the "learning fringe."
Cognitive Bias	Accurate self-assessment; Objective inquiry.	**Calibration Curves:** Detecting Overconfidence. **Search Log Analysis:**

		Detecting Confirmation Bias.

Key Data Sources:

- **Cognitive Load & Dynamics:** [10]
- **Dual-Process & Spaced Repetition:** [20]
- **Mental Models & Knowledge Graphs:** [1]
- **Bias Detection:** [35]
- **Adaptive Architectures:** [1]

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