

Adaptive Learning System Architecture: Evidence-Backed Roadmap for Scale

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Abstract

This document presents a comprehensive, incremental architecture for an adaptive learning system designed to serve millions of higher education learners. The system delivers micro-learning resources (short video clips and PDF segments) in response to student questions, provides formative assessments, and measures learning gains over time. We compare four architectural approaches, recommend a hybrid RAG-first strategy with bandit-based optimization, and provide a detailed 12-week implementation roadmap with concrete metrics, risks, and mitigation strategies. The architecture prioritizes measurable learning outcomes over engagement metrics and maintains agility for foundation model upgrades.

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1 Executive Summary

1.1 Chosen Approach and Rationale

- **Recommended Architecture:** RAG-first with cross-encoder reranking, agentic orchestration, and contextual bandits for content selection, augmented with task-specific LoRA fine-tuning for pedagogical components.
- **Why This Beats Alternatives:** Addresses cold-start problem for content recommendation (no historical labels), leverages existing Q&A/assessment data, enables rapid iteration, maintains model-agnostic flexibility, and provides clear pathway from baseline to optimized system.
- **Cold-Start Strategy:** Start with metadata-driven heuristics and semantic similarity (no ML needed), rapidly collect preference data through teacher-in-the-loop and implicit feedback, bootstrap bandit policies within 4–6 weeks.
- **Minimality Enforcement:** Hard constraints on resource duration/length, explicit sufficiency scoring (semantic coverage per unit time/pages), segment-level retrieval instead of whole assets, MMR diversification to avoid redundancy.
- **Learning Measurement:** IRT-based ability estimation (θ), calibrated item parameters (discrimination a , difficulty b), longitudinal $\Delta\theta$ tracking, normalized gain metrics that distinguish learning from engagement (time-on-task, clicks).
- **Pedagogical Quality:** Few-shot prompted question generation aligned to Bloom taxonomy levels, rubric-based grading with reference answers, distractor quality checks, hint generation, worked examples for scaffolding.
- **Data Flywheel:** Existing Q&A logs seed question generation models, assessment data calibrates difficulty estimators, user interactions train bandit policies, teacher feedback refines retrieval quality through active learning.
- **Risk Mitigation:** Retrieval-grounded generation to reduce hallucinations, answerability checks before question generation, refusal paths for out-of-scope queries, privacy-preserving logging, drift detection for item parameters.
- **Agility Preserved:** LoRA adapters (not full fine-tuning) for pedagogical tasks, modular architecture allows component swaps, evaluation harness enables A/B testing of model upgrades, prompt libraries versioned alongside models.
- **Team Fit:** Leverages agentic AI expertise for orchestration, data science skills for IRT calibration and bandit tuning, avoids heavy ML engineering burden (no custom training infrastructure), uses standard RAG tooling and off-the-shelf LLMs.

2 Architecture Options Comparison

We evaluate four architectural approaches across key dimensions relevant to our constraints and team capabilities.

2.1 Option A: RAG-First + Reranking + Agentic Orchestration

Components:

- Bi-encoder (dense) + BM25 (sparse) hybrid retrieval over chunked content corpus
- Cross-encoder reranker for top-k candidates
- MMR (Maximal Marginal Relevance) for diversity
- LLM-based agentic planner: query understanding → retrieval → content selection → pedagogy tools → evaluation → next-action
- Prompt engineering for question generation, grading, hint provision

Infrastructure:

- Vector database (Pinecone, Weaviate, or Qdrant): \$500–\$2k/month at prototype scale
- LLM API (GPT-4o, Claude Sonnet, Gemini): \$0.01–0.03/1k tokens
- Embedding API (OpenAI text-embedding-3, Cohere): \$0.0001–0.0002/1k tokens
- Cross-encoder inference (can self-host small models like ms-marco-MiniLM-L-12)

Cost Estimate (10k learners, 5 interactions/day):

- Embeddings: ~\$50/month
- LLM calls: ~\$1,500–\$3,000/month
- Vector DB: ~\$500–\$1,000/month
- Total: \$2,000–\$4,500/month at prototype scale

Latency:

- Retrieval (hybrid + rerank): 200–500ms
- LLM generation (streaming): 1–3s to first token, 3–8s total
- End-to-end: 4–10s for full interaction

Data Needs:

- Minimal for cold-start: content corpus only
- No labeled training data required
- Can start immediately with existing materials

Expected Quality:

- Retrieval: 70–85% Recall@10 with hybrid search
- Question quality: 60–75% expert approval (prompt-only)
- Minimality: Depends on prompting and post-processing
- Learning gains: Baseline to improve upon

Cold-Start Viability: **Excellent** – Works day-one with zero historical labels

Expected Learning Impact: Moderate (depends on content quality and prompt engineering)

Team Fit: **Excellent** – Matches agentic AI expertise, no ML training required

Risks:

- Prompt brittleness across domains
- No learning from user feedback (static)
- Hallucination risk if retrieval fails
- Cost scales linearly with usage

2.2 Option B: Lightweight Fine-Tuning (LoRA/PEFT) + RAG

Components:

- Same RAG stack as Option A
- LoRA adapters for: (1) question generation, (2) rubric-based grading, (3) distractor generation, (4) pedagogical style (hints, explanations)
- Base models: Llama 3.1 70B, Mistral Large, or GPT-4o
- Adapter inference via vLLM or Lorax for efficient serving

Infrastructure:

- Same vector DB as Option A
- LoRA training: 1–2x A100 GPUs for 4–12 hours per adapter (\$50–\$200/training run on cloud)
- Inference: Self-hosted vLLM on 2–4x A100s or API with adapters
- Storage for adapters: <1GB per adapter

Cost Estimate:

- Training: \$500–\$1,500 one-time per adapter (4 adapters → \$2k–\$6k)
- Inference (self-hosted): \$2,000–\$4,000/month GPU costs
- OR API + adapters: Similar to Option A + adapter overhead
- Total: \$2,500–\$5,000/month ongoing

Latency:

- Similar to Option A (adapter adds <50ms)
- Self-hosting can reduce latency by 500–1000ms vs. API

Data Needs:

- Minimum 500–2,000 high-quality examples per task
- Existing Q&A/assessment logs provide seed data for question generation and grading
- Need manual labeling for distractor quality and pedagogical style (1–2 weeks of expert time)

Expected Quality:

- Question quality: 75–90% expert approval (10–15% boost over prompting)
- Grading consistency: 85–95% agreement with human rubrics
- Distractor quality: Significant improvement in plausibility
- Learning gains: 5–15% improvement over prompt-only baseline (estimated)

Cold-Start Viability: **Moderate** – Requires 2–4 weeks for data collection + training

Expected Learning Impact: High (task-specific optimization improves pedagogical quality)

Team Fit: **Good** – Data scientists can handle LoRA training, less complex than full FT

Risks:

- Adapter drift when base models update
- Need retraining cadence (every 6–12 months)
- Overfitting if training data not diverse enough
- Inference complexity (managing multiple adapters)

2.3 Option C: RL/Bandits for Content Selection + RAG Baseline

Components:

- Option A (RAG-first) as baseline retrieval and pedagogy
- Contextual bandit layer on top: learns which content chunks maximize learning + minimality
- Context: student ability θ , query embedding, prior performance, resource metadata
- Actions: select from top-k retrieved candidates
- Reward: $R = w_1 \cdot \Delta\theta + w_2 \cdot \text{brevity} - w_3 \cdot \text{irrelevance}$
- Start with Thompson Sampling or UCB, graduate to offline RL if sufficient data

Infrastructure:

- Same as Option A for RAG
- Bandit policy server: lightweight (Redis + Python service)

- Logging infrastructure: event stream (Kafka/Kinesis) + data warehouse
- Offline evaluation: IPS/DR estimators, simulator for policy testing

Cost Estimate:

- Incremental over Option A: \$200–\$500/month for bandit infra
- Data storage/processing: \$100–\$300/month
- Total: \$2,300–\$5,000/month

Latency:

- Policy inference: <50ms (table lookup or simple model)
- Total latency: Same as Option A + 50ms

Data Needs:

- Cold-start: Can use uniform random or heuristic policy for 2–4 weeks
- Training data: Needs 10k–50k logged interactions before policy improves over heuristics
- Continuous feedback loop essential

Expected Quality:

- Retrieval/selection: 10–25% improvement over static ranking after sufficient data
- Minimality: Direct optimization via reward leads to 15–30% shorter resources
- Learning gains: 10–20% improvement over non-personalized baseline (after convergence)

Cold-Start Viability: **Moderate** – Starts with heuristics, improves over 4–8 weeks

Expected Learning Impact: Very High (directly optimizes for learning outcomes)

Team Fit: **Good** – Data scientists have expertise; bandit theory is mature

Risks:

- Delayed reward signal (learning happens over days/weeks)
- Need careful reward design to avoid gaming (e.g., always selecting shortest resources)
- Off-policy evaluation is noisy; need large sample sizes
- Safety constraints (prevent over-exploration of bad content)

2.4 Option D: Fully Fine-Tuned Task-Specific Models

Components:

- Small, specialized models (1–13B parameters) fully fine-tuned for each task
- Question generator: Llama 3.1 8B fine-tuned on 10k+ exemplars
- Grader: T5-XXL fine-tuned on rubric-scored responses

- Distractor generator: GPT-2 or Llama 7B fine-tuned
- Content selector: Cross-encoder fine-tuned on relevance labels
- RAG uses standard retrieval (no fine-tuning)

Infrastructure:

- Training: 4–8x A100s for 1–3 days per model (\$500–\$2,000/model)
- Inference: Self-hosted on 2–4x GPUs or use smaller models on CPU
- Model storage: 5–50GB per model

Cost Estimate:

- Training: \$2,000–\$8,000 one-time (4 models)
- Inference: \$1,500–\$3,000/month (self-hosted) or \$500–\$1,000/month (small models)
- Total: \$1,500–\$3,000/month ongoing

Latency:

- Small models: 100–500ms per task
- Can pipeline tasks in parallel
- Total: 2–5s (faster than large LLM)

Data Needs:

- Highest data requirements: 10k–50k examples per task
- Months of manual labeling effort
- Existing Q&A logs insufficient without heavy curation

Expected Quality:

- Potentially highest quality for specific tasks (90–95% on benchmarks)
- Consistency and reliability superior to prompting
- But: brittle to domain shifts, requires retraining for new content types

Cold-Start Viability: **Poor** – Requires 2–6 months of data collection + training

Expected Learning Impact: High (once trained), but delayed

Team Fit: **Moderate** – Requires ML engineering, GPU infrastructure, complex training pipelines

Risks:

- Long time-to-value (3–6 months before deployment)
- Model maintenance burden (multiple models to version and monitor)
- Overfitting to training distribution
- Difficult to iterate (retraining is slow and expensive)
- Loss of flexibility as foundation models improve

2.5 Comparison Table

Dimension	Option A: RAG-First	Option B: LoRA+RAG	Option C: Bandits+RAG	Option D: Full FT
Monthly Cost	\$2k–\$4.5k	\$2.5k–\$5k	\$2.3k–\$5k	\$1.5k–\$3k
Latency	4–10s	4–10s	4–10s	2–5s
Data Needs	None (zero-shot)	0.5k–2k per task	10k–50k interactions	10k–50k per task
Time to Deploy	1–2 weeks	4–6 weeks	2 weeks (baseline) + 6–8 weeks (optimized)	3–6 months
Cold-Start Viability	Excellent	Moderate	Moderate	Poor
Learning Impact	Baseline (60–70%)	High (75–85%)	Very High (80–90%)	High (85–95%, delayed)
Team Fit	Excellent	Good	Good	Moderate
Agility	High (prompt changes only)	High (swap adapters)	Moderate (policy updates)	Low (retrain required)
Scalability	Linear API costs	GPU costs + some API	Similar to A + bandit overhead	Self-hosted, lower marginal cost
Risks	Hallucinations, prompt drift	Adapter-model mismatch	Reward design, delayed feedback	Long dev cycle, brittleness

Table 1: Architecture Options Comparison

2.6 Recommendation

Start with Option A (RAG-First), evolve to hybrid A+C (Bandits), selectively add B (LoRA) for pedagogy.

Rationale:

1. **Cold-start imperative:** We have no historical content recommendation labels. Option A works immediately.
2. **Rapid learning:** Option C (bandits) can start collecting data from day one on top of Option A baseline.
3. **Strategic fine-tuning:** Option B (LoRA) addresses pedagogical quality after we validate baseline retrieval works.
4. **Avoid premature optimization:** Option D locks us into brittle, expensive models before we understand the problem.
5. **Agility:** A+B+C keeps us model-agnostic and able to upgrade foundation models.

3 Final Recommended Architecture

3.1 System Overview

The recommended architecture is a modular, layered system that combines:

1. **Hybrid Retrieval Layer:** BM25 + dense embeddings with cross-encoder reranking
2. **Content Minimization Layer:** Segment detection, sufficiency scoring, length constraints
3. **Pedagogical Layer:** Question generation, rubric grading, hint provision, worked examples
4. **Assessment & Analytics:** IRT-based ability estimation, item calibration, learning gain tracking
5. **Agentic Orchestration:** Multi-step planner coordinating retrieval, selection, pedagogy, evaluation
6. **Bandit Optimization:** Contextual bandits for content selection under multi-objective reward

3.2 Architecture Diagram

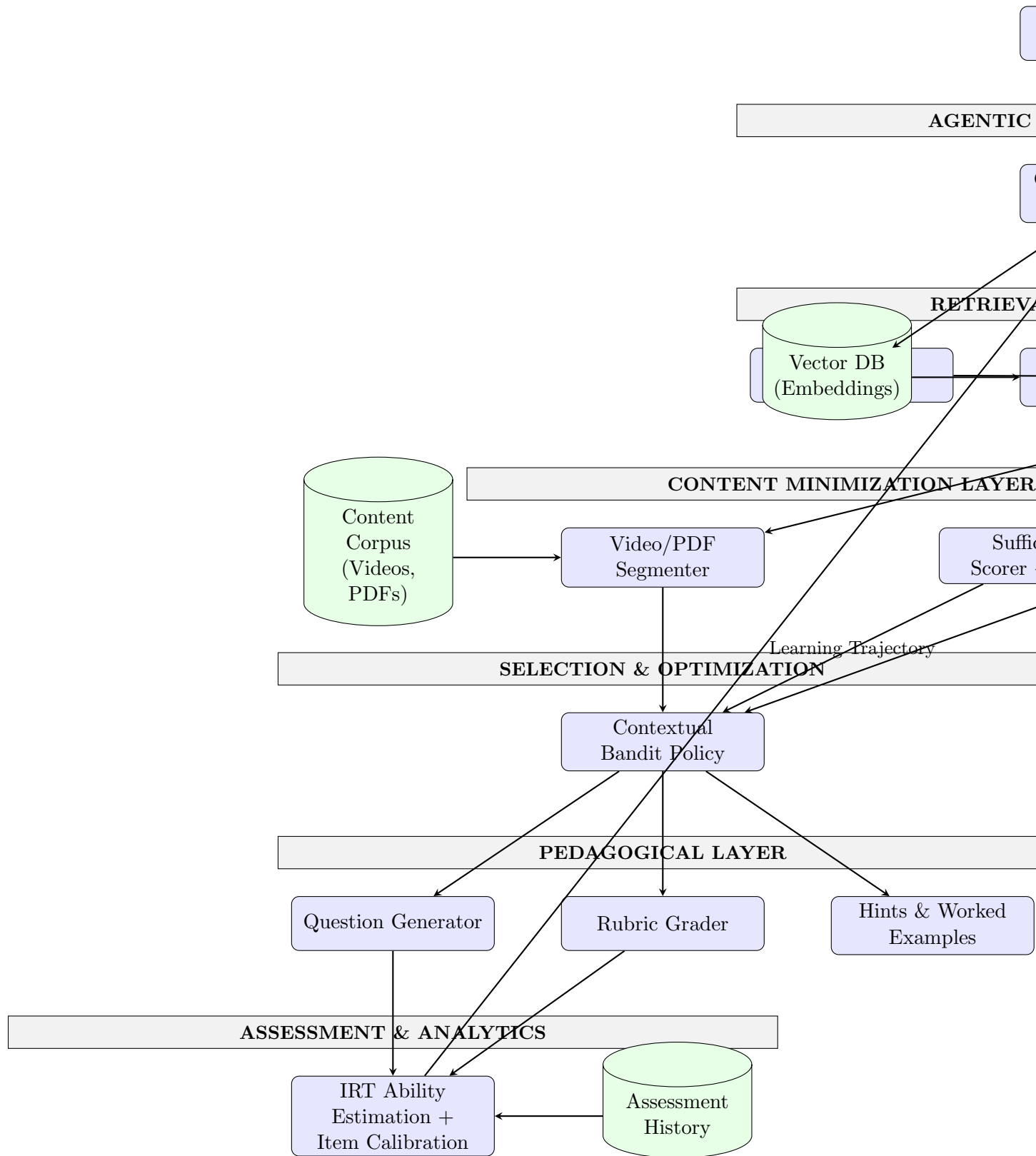


Figure 1: Recommended System Architecture

3.3 Component Specifications

3.3.1 Retrieval Layer

Embedding Model:

- Primary: OpenAI `text-embedding-3-large` (3,072 dimensions) or Cohere `embed-v3`
- Alternative: Open-source `bge-large-en-v1.5` or `e5-mistral-7b-instruct` (self-hosted)
- Rationale: Strong performance on semantic search, handles educational content well

Chunking Strategy:

- Videos: Segment by ASR sentence boundaries + scene changes, 30–180 second chunks
- PDFs: Paragraph-level chunks (100–500 tokens), preserve section context in metadata
- Overlap: 20% overlap between chunks to preserve context
- Metadata: Title, section, page/timestamp, content type, duration/length, keywords

Hybrid Search:

- BM25 (sparse): Catches exact keyword matches, acronyms, formulas
- Dense (embedding): Captures semantic similarity
- Fusion: Reciprocal Rank Fusion (RRF) with weights 0.3 (BM25) + 0.7 (dense)
- Retrieve top-50 from each, fuse to top-20 for reranking

Cross-Encoder Reranking:

- Model: `ms-marco-MiniLM-L-12-v2` or `bge-reranker-large`
- Input: [query, candidate_chunk] pairs
- Output: Relevance score 0–1
- Rerank top-20 to top-5 for content minimization layer

MMR (Maximal Marginal Relevance):

- Apply after reranking to ensure diversity
- $MMR(D_i) = \lambda \cdot \text{Sim}(D_i, Q) - (1 - \lambda) \cdot \max_{D_j \in S} \text{Sim}(D_i, D_j)$
- $\lambda = 0.7$ (balance relevance and diversity)
- Select top-3 diverse candidates for presentation

3.3.2 Content Minimization Layer

Video Segmentation:

- ASR: Whisper (OpenAI) or AssemblyAI for transcription
- Scene detection: PySceneDetect or TransNetV2 for visual boundaries
- Semantic chunking: Combine ASR sentence boundaries + scene changes + silence detection
- Target: 30–180 second clips (hard maximum: 3 minutes)
- Timestamp alignment: Map chunks to video timecodes for clip extraction

PDF Section Detection:

- Parsing: PyMuPDF or Apache PDFBox for structured extraction
- Section headers: Regex + font size analysis to identify hierarchy
- Paragraph boundaries: Whitespace and formatting cues
- Target: 0.5–2 page segments (hard maximum: 3 pages)
- Extract images/figures with captions

Sufficiency Scoring:

- **Semantic Coverage:** $\text{Coverage}(R, Q) = \frac{\text{cosine}(\text{embed}(R), \text{embed}(Q))}{\text{duration}(R) \text{ or } \text{pages}(R)}$
- **Redundancy Penalty:** Penalize chunks with high overlap to already-selected content
- **Clarity Score:** LLM-based (few-shot) assessment of pedagogical clarity (0–10 scale)
- **Final Score:** $S = 0.5 \cdot \text{Coverage} + 0.3 \cdot \text{Clarity} - 0.2 \cdot \text{Redundancy}$
- Select top-1 to top-3 segments with highest sufficiency scores

Summarization to Micro-Nuggets:

- For longer segments (≥ 2 min or ≥ 1 page), provide extractive or abstractive summary
- Key points: 3–5 bullet points capturing main ideas
- Learner can choose: (1) summary + link to full segment, or (2) full segment directly

3.3.3 Pedagogical Layer

Question Generation:

- **Prompt-based (Milestone 3):** Few-shot examples aligned to Bloom taxonomy (Remember, Understand, Apply, Analyze, Evaluate, Create)
- **LoRA fine-tuned (Milestone 5):** Llama 3.1 8B with 500–2k exemplars from existing Q&A logs
- **Inputs:** Learning resource content, student query, desired Bloom level, prior performance

- **Outputs:** Question text, answer key, distractor options (for MCQ), rubric (for open-ended)
- **Validation:** Answerability check (can question be answered from resource?), factuality check (grounded in content?)

Rubric-Based Grading:

- **Rubric design:** 3–5 levels (Novice, Developing, Proficient, Advanced), explicit criteria per level
- **Grading prompt:** Chain-of-thought reasoning with rubric, reference answer, and student response
- **LoRA fine-tuning (optional):** On 1k–2k graded examples with expert annotations
- **Confidence scoring:** Model outputs confidence 0–1; defer to human if confidence < 0.7

Hints & Worked Examples:

- **Progressive hints:** Graduated scaffolding (conceptual hint → procedural hint → partial solution)
- **Worked examples:** Step-by-step solution to similar problem with annotations
- **Trigger:** Provide hints after 1–2 incorrect attempts or explicit student request

Distractor Generation (MCQ):

- **Quality criteria:** Plausible but incorrect, target common misconceptions, vary in difficulty
- **Generation:** Prompt or fine-tuned model with misconception database
- **Validation:** Expert review (10% sample), pilot testing with learners

3.3.4 Assessment & Analytics Layer

IRT (Item Response Theory) Ability Estimation:

- **Model:** 3PL (3-Parameter Logistic): $P(\theta, a, b, c) = c + \frac{1-c}{1+e^{-a(\theta-b)}}$
- θ : Learner ability, a : Item discrimination, b : Item difficulty, c : Guessing parameter
- **Estimation:** Maximum Likelihood Estimation (MLE) or Expected A Posteriori (EAP) for θ
- **Item calibration:** Marginal Maximum Likelihood (MML) using response data from all learners

Question Difficulty Calibration:

- **Initial estimate:** Weak labels from expert judgment (1–10 scale) or readability scores
- **Pilot phase:** Administer to diverse learners (n=50–200), collect response patterns
- **Calibration:** Run IRT parameter estimation (EM algorithm) on pilot data
- **Update cadence:** Recalibrate every 500 responses per item or quarterly

Learning Gain Measurement:

- **Primary metric:** $\Delta\theta = \theta_{\text{post}} - \theta_{\text{pre}}$ over study session or week
- **Normalized gain:** $g = \frac{\theta_{\text{post}} - \theta_{\text{pre}}}{\theta_{\text{max}} - \theta_{\text{pre}}}$ (Hake gain)
- **Mastery progression:** % of items at target proficiency level (e.g., $P(\theta) > 0.7$)
- **Longitudinal tracking:** Plot $\theta(t)$ over weeks/months, detect plateaus or regression

Distinguish Engagement from Learning:

- **Engagement metrics:** Time-on-task, click-through rate, completion rate (log but don't optimize for)
- **Learning metrics:** $\Delta\theta$, quiz accuracy uplift, downstream task performance
- **Correlation analysis:** Monitor correlation; high engagement + low $\Delta\theta$ signals ineffective content

3.3.5 Agentic Orchestration**Planner:**

- **Input:** Student query, current θ estimate, prior interaction history, available tools
- **Output:** Execution plan: (1) parse query intent, (2) retrieve candidates, (3) select best resource, (4) deliver + formative assessment, (5) evaluate response, (6) plan next resource
- **Implementation:** ReAct-style prompting or LangGraph for multi-step orchestration

Tool Inventory:

- `retrieve_content(query, filters)`: Hybrid search + reranking
- `segment_resource(resource_id, target_length)`: Video/PDF chunker
- `score_sufficiency(segments, query)`: Sufficiency scorer
- `select_content(candidates, policy)`: Bandit policy or heuristic
- `generate_question(resource, bloom_level)`: Question generator
- `grade_response(question, response, rubric)`: Rubric grader
- `provide_hint(question, attempt_history)`: Hint generator
- `update_ability(learner_id, response_data)`: IRT updater
- `plan_next_resource(learner_state, goals)`: Next-action planner

Execution Flow:

1. Planner receives query, retrieves learner state (θ , history)
2. Calls `retrieve_content` → top-20 candidates

3. Calls `segment_resource + score_sufficiency` \rightarrow top-3 segments
4. Calls `select_content` (bandit) \rightarrow 1 segment
5. Delivers resource to learner
6. Calls `generate_question` \rightarrow formative question
7. Learner responds
8. Calls `grade_response` \rightarrow correctness + feedback
9. Calls `update_ability` \rightarrow new θ estimate
10. Calls `plan_next_resource` based on $\Delta\theta$ and mastery gaps

3.3.6 Bandit Optimization Layer

Contextual Bandit Setup:

- **Context:** $x = [\theta, \text{query_embedding}, \text{prior_performance}, \text{resource_metadata}]$
- **Actions:** $A = \{\text{segment}_1, \text{segment}_2, \dots, \text{segment}_k\}$ (top-k from retrieval)
- **Reward:** $R = w_1 \cdot \Delta\theta + w_2 \cdot \text{brevity_bonus} - w_3 \cdot \text{irrelevance_penalty} - w_4 \cdot \text{latency_cost}$
- **Policy:** $\pi(a|x)$ maps context to action (content selection)

Reward Components:

- $\Delta\theta$: Change in ability after learning session (proxy: quiz accuracy if θ not yet calibrated)
- Brevity bonus: $\max(0, \frac{T_{\text{target}} - T_{\text{actual}}}{T_{\text{target}}})$ where T is duration/length
- Irrelevance penalty: $1 - \text{cosine}(\text{resource}, \text{query})$ (semantic alignment)
- Latency cost: $\frac{\text{response_time}}{10 \text{ seconds}}$ (normalized)
- **Weights:** $w_1 = 1.0, w_2 = 0.3, w_3 = 0.5, w_4 = 0.1$ (tune via Pareto frontier analysis)

Algorithm:

- **Cold-start (Weeks 1–4):** Thompson Sampling with Beta priors, uniform exploration
- **Warm-up (Weeks 5–8):** LinUCB or Neural UCB with context features
- **Maturity (Weeks 9+):** Offline RL (DQN or BCQ) trained on logged data, online fine-tuning

Off-Policy Evaluation:

- Inverse Propensity Scoring (IPS): $\hat{V}(\pi) = \frac{1}{n} \sum_{i=1}^n \frac{\pi(a_i|x_i)}{\pi_0(a_i|x_i)} r_i$
- Doubly Robust (DR): Combines IPS with model-based estimates for lower variance
- Simulator: Replay historical interactions under new policy for what-if analysis

Safety Constraints:

- Minimum exploration rate: 10% (always try random actions to discover new content)
- Blacklist: Flag and exclude resources with negative feedback (thumbs-down, low $\Delta\theta$)
- Per-resource quotas: Limit exposure to any single resource to avoid overfitting policy
- Teacher override: Human-in-the-loop to veto policy decisions during pilot

3.4 Guardrails & Safety**Retrieval-Grounded Generation:**

- All LLM outputs cite source chunks (IDs, timestamps)
- Factuality check: Verify claims against retrieved content using NLI model
- Contradiction detection: Flag if LLM output contradicts source material

Answerability Checks:

- Before generating questions, verify: "Can this question be answered from the provided resource?"
- Use LLM self-critique: "Given resource R, is question Q answerable? Yes/No + reasoning"
- If unanswerable, regenerate or defer

Refusal Paths:

- Detect out-of-scope queries (off-topic, harmful, non-educational)
- Polite refusal: "I can help with [list of topics]. Your question about [X] is outside my scope."
- Fallback to human tutor if available

JSON Schema Validation:

- All structured outputs (questions, rubrics, plans) validated against JSON schemas
- Reject malformed outputs, retry with schema instructions

Privacy & PII Protection:

- No learner PII (names, emails) in LLM prompts or logs
- Use anonymized IDs (`learner_id = hash(email)`)
- Role-based access: Only educators/admins see identifiable data
- On-prem deployment option for institutions with strict privacy requirements

3.5 Telemetry & Monitoring

Per-User Dashboards:

- Learning trajectory: $\theta(t)$ over time with confidence intervals
- Mastery map: Heatmap of topics \times proficiency levels
- Engagement metrics: Time-on-task, session frequency
- Resource exposure: Types and durations of consumed content

System-Level Metrics:

- Retrieval quality: nDCG@5, Recall@10, mean reciprocal rank (MRR)
- Minimality: Median resource length, overkill rate (% over target length)
- Question quality: Expert approval rate, factuality score
- Grading consistency: Inter-rater agreement (Krippendorff's α)
- IRT stability: θ standard error (SE), item parameter drift
- Bandit diagnostics: Exploration rate, policy entropy, regret bounds
- Safety incidents: Hallucination rate, refusal accuracy, complaint rate

Alerts:

- θ SE > 0.5 (low confidence in ability estimate)
- Item difficulty drift > 0.2 units/month (needs recalibration)
- Bandit policy entropy < 0.5 (exploitation too aggressive)
- Hallucination rate $> 5\%$ (content quality issue)
- P95 latency > 15 seconds (performance degradation)

Stakeholder Views:

Educator Dashboard:

- Class-level: Average θ , $\Delta\theta$, mastery rates per topic
- Individual learner drill-down: Trajectory, struggling topics, intervention recommendations
- Content analytics: Which resources are most/least effective (by $\Delta\theta$)
- Question bank review: Flag low-discrimination or misaligned items

Learner Explanations:

- "Why this resource?": "This 2-minute video segment covers [concept] at your current proficiency level."
- "Why this question?": "This question assesses [skill] at the Apply level of Bloom's taxonomy."
- "What's next?": "Based on your performance, I recommend: [next topic/skill] to build on [current mastery]."

4 Data Plan: Cold-Start to Flywheel

4.1 Challenge: No Historical Content Recommendation Labels

We have:

- ✓ Content corpus (videos, PDFs) with metadata (title, topic, duration/length)
- ✓ Historical Q&A logs (student questions, instructor answers)
- ✓ Historical assessment data (questions, responses, correctness)

We lack:

- × Explicit labels: "For query Q, resource R is the best/shortest/most relevant"
- × Implicit feedback: clicks, dwell time, learner ratings on recommended content

4.2 Cold-Start Strategy (Weeks 1–4)

4.2.1 Heuristic Baseline

Step 1: Metadata Filters

- Tag content with keywords/topics (manual or LLM-based auto-tagging)
- Extract query intent → match to content tags
- Filter: Duration ≤ 3 min (videos), Length ≤ 2 pages (PDFs)
- Rank by: (1) tag overlap, (2) brevity, (3) popularity (if view counts available)

Step 2: Semantic Coverage (Zero-Shot)

- Embed query and all candidate chunks
- Compute cosine similarity: $\text{sim}(q, c_i)$
- Coverage-per-unit: $\frac{\text{sim}(q, c_i)}{\text{duration}(c_i)}$ or $\frac{\text{sim}(q, c_i)}{\text{pages}(c_i)}$
- Select top-3 by coverage-per-unit

Step 3: ASR + Sectionizer

- Videos: ASR transcript → chunk by sentences/scenes → embed chunks → retrieve top-k
- PDFs: Extract sections → embed paragraphs → retrieve top-k
- Sufficiency check: LLM judges "Does this segment answer the query? Yes/No + confidence"
- If confidence < 0.7 , try next candidate

Expected Performance:

- Retrieval Recall@10: 60–75% (decent but not great)
- Minimality: 70–80% under target length (heuristics enforce hard caps)
- User satisfaction: Baseline to improve upon

4.2.2 Weak Labels from Existing Data

Source 1: Q&A Logs

- Historical: Student asked Q, instructor provided answer A
- Heuristic: Find content chunks that match A (high similarity)
- Weak label: "For query Q, chunk C (matching A) is relevant"
- Caveat: Instructors may cite external resources not in our corpus
- Validation: Sample 100 cases, manually verify label quality

Source 2: Assessment Data

- Historical: Question q assesses concept c
- Weak label: "Content chunks explaining concept c are relevant for queries about c "
- Build concept \rightarrow content mapping via topic modeling or LLM classification

Source 3: Content Transcripts + Question Overlap

- If video transcript or PDF text contains terms/phrases from historical questions, likely relevant
- TF-IDF or BM25 to find high-overlap chunks

Dataset Size: 5k–20k weakly labeled (query, relevant_chunk) pairs

4.2.3 Teacher-in-the-Loop Labeling

Active Learning Protocol:

1. System retrieves top-5 candidates for a query using heuristics
2. Present to expert educator: "For query Q, rank these 5 resources by relevance + minimality"
3. Expert provides: (1) ranking, (2) binary label (good/bad), (3) optional notes
4. Prioritize uncertain cases: Low confidence, low coverage, diverse query types

Labeling Sprint (Week 1–2):

- Goal: 500–1,000 high-quality labels
- Team: 2–3 educators, 2–4 hours/day
- Interface: Simple web form with query, candidates, ranking inputs
- Quality control: 10% overlap for inter-rater agreement (target Krippendorff's $\alpha > 0.7$)

Rubric for "Best Minimal Resource":

1. **Relevance:** Directly answers the query (5 = perfect, 1 = off-topic)
2. **Minimality:** Shortest duration/length that covers the question (5 = minimal, 1 = excessive)

3. **Clarity:** Pedagogically clear, well-explained (5 = excellent, 1 = confusing)
4. **Correctness:** Factually accurate (5 = correct, 1 = errors/misleading)

Inter-Rater Agreement:

- Measure: Krippendorff's α or Fleiss' κ on overlap subset
- Target: $\alpha > 0.7$ (acceptable), $\alpha > 0.8$ (good)
- If $\alpha < 0.7$: Refine rubric, provide calibration examples, re-train raters

4.3 Rapid Dataset Creation (Weeks 3–6)

4.3.1 Offline Labeling Campaign

Scale Up:

- Recruit 5–10 educators (internal or contract)
- Labeling platform: Label Studio, Prodigy, or custom React app
- Batch size: 50–100 queries per educator per week
- Target: 2,000–5,000 labels in 4 weeks

Sampling Strategy:

- Stratify by: (1) query complexity (simple fact \rightarrow complex concept), (2) topic area, (3) resource type (video/PDF)
- Over-sample edge cases: Ambiguous queries, multiple plausible answers, very short/long resources
- Include negative examples: Clearly irrelevant resources (for classifier calibration)

Quality Assurance:

- Weekly calibration sessions: Discuss disagreements, update rubric
- Random audits: Senior educator reviews 10% of labels for correctness
- Automatic checks: Flag outliers (e.g., label contradicts semantic similarity)

4.3.2 Synthetic Data Augmentation

LLM-Generated Queries:

- For each content chunk, generate 3–5 plausible student questions
- Prompt: "Given this video segment, what questions would a student ask to learn this content?"
- Validation: Expert review 20% sample for realism and relevance
- Synthetic pairs: (generated_query, source_chunk) \rightarrow 10k–50k pairs

Paraphrasing Existing Queries:

- Take historical Q&A queries, generate paraphrases via LLM or back-translation
- Preserves intent, increases query diversity
- Expands dataset by 2–3x

Caveat: Synthetic data has distribution shift risk. Use for augmentation, not replacement.

4.4 Using Existing Q&A/Assessment Logs**4.4.1 Question Generation Training Data**

Source: Historical assessment database (10k–100k questions)

Preprocessing:

- Filter: Remove low-quality (typos, ambiguous), off-topic, or obsolete questions
- Annotate: Bloom level (manual or LLM-based classification)
- Map to content: Link question to content chunk(s) that explain the answer

Training Corpus:

- Format: (content_chunk, bloom_level, question, answer, distractors)
- Size: 1k–5k high-quality exemplars (post-filtering)
- Use for: Few-shot prompting (Milestone 3), LoRA fine-tuning (Milestone 5)

4.4.2 Grading Rubric Training Data

Source: Historical student responses + instructor grades/feedback

Preprocessing:

- Extract: (question, student_response, score, rubric_level, instructor_feedback)
- Standardize rubrics: Map to common scale (Novice/Developing/Proficient/Advanced)
- Clean: Remove responses with insufficient instructor feedback

Training Corpus:

- Format: (question, rubric, student_response, ground_truth_level, rationale)
- Size: 2k–10k graded responses
- Use for: Prompt engineering with exemplars, LoRA fine-tuning

4.4.3 Difficulty Estimation Calibration

Source: Historical response data (learner_id, question_id, correct/incorrect, response_time)

IRT Calibration:

- Run MML estimation (EM algorithm) on historical data
- Obtain: (a, b, c) parameters for each item, θ for each learner
- Validate: Holdout test set, check model fit (RMSE, AIC, BIC)

Cold-Start for New Items:

- Expert judgment: Rate difficulty 1–10, map to b estimate
- Pilot: Administer to 50–200 learners, update parameters
- Anchor items: Include calibrated items in each test to link scales

4.5 Data Flywheel (Weeks 7+)

4.5.1 Implicit Feedback Collection

User Actions:

- Click-through: Learner selects a recommended resource
- Dwell time: Duration spent on resource (proxy for relevance)
- Skip: Learner skips to next resource (negative signal)
- Thumbs up/down: Explicit feedback on resource quality
- Quiz performance: Correctness on formative questions (learning outcome proxy)

Logging:

- Event: (timestamp, learner_id, query, recommended_resources, selected_resource, dwell_time, quiz_score, feedback)
- Storage: Event stream (Kafka) \rightarrow Data warehouse (Snowflake, BigQuery)
- Retention: 1 year minimum for analysis

4.5.2 Bandit Policy Training

Data Preparation:

- Context: $x = [\theta, \text{query_embedding}, \text{resource_metadata}]$
- Action: $a = \text{selected_resource_id}$
- Reward: $r = w_1 \cdot \text{quiz_score_uplift} + w_2 \cdot \text{brevity_bonus} - w_3 \cdot \text{skip_penalty}$
- Propensity: $\pi_0(a|x)$ from baseline heuristic policy

Training Cadence:

- Week 1–4: Collect data under heuristic policy (10k–50k interactions)
- Week 5: Train initial bandit (Thompson Sampling with historical data)
- Week 6–8: Deploy bandit, collect more data (exploration rate = 20%)
- Week 9+: Retrain weekly with cumulative data, reduce exploration to 10%

4.5.3 Retrieval Quality Improvement

Relevance Feedback:

- Positive: Learner clicks + high dwell time + thumbs-up → boost rank
- Negative: Skip + thumbs-down → demote rank
- Retraining: Fine-tune cross-encoder on (query, clicked_resource, label) pairs every month

Active Learning:

- Identify uncertain cases: Low cross-encoder score but high user engagement (or vice versa)
- Send to expert for labeling: "Is resource R relevant for query Q?"
- Retrain with new labels → improved reranker

4.5.4 Question Quality Refinement

Expert Review Loop:

- Weekly: Sample 50–100 generated questions
- Educators rate: Clarity, alignment, factuality (1–5 scale)
- Low-rated questions → analyze failure modes (ambiguous, off-topic, factually wrong)
- Update: Refine prompts or add to LoRA training set

Learner Feedback:

- Flag button: "This question is confusing/incorrect"
- Aggregate flags → prioritize for review
- Retire low-quality questions, replace with improved versions

4.6 Data Plan Summary

Phase	Data Sources	Methods	Timeline
Cold-Start (W1–4)	Content metadata, ASR, weak labels from Q&A logs	Heuristics, semantic similarity, teacher-in-the-loop (500–1k labels)	Weeks 1–4
Rapid Dataset (W3–6)	Offline labeling (2k–5k), synthetic queries (10k–50k)	Active learning, LLM augmentation, quality checks	Weeks 3–6
Existing Logs (W1–6)	Historical Q&A (10k–100k), assessments (10k–100k)	IRT calibration, question/rubric corpus creation	Weeks 1–6
Flywheel (W7+)	Implicit feedback (clicks, dwell, quiz scores), explicit feedback (thumbs)	Bandit training, retrieval fine-tuning, question refinement	Weeks 7+ (ongoing)

Table 2: Data Plan Timeline

5 Metrics & Evaluation

All metrics must be **executable per milestone** with concrete measurement protocols.

5.1 Retrieval & Selection Quality

5.1.1 nDCG@k (Normalized Discounted Cumulative Gain)

Definition:

$$\text{nDCG@k} = \frac{\text{DCG@k}}{\text{IDCG@k}}, \quad \text{DCG@k} = \sum_{i=1}^k \frac{2^{\text{rel}_i} - 1}{\log_2(i + 1)}$$

Measurement:

- Expert labels: For 200–500 test queries, rate top-10 retrieved resources (relevance 0–3)
- Compute nDCG@5, nDCG@10
- **Baseline target:** nDCG@5 > 0.6, nDCG@10 > 0.65
- **Optimized target:** nDCG@5 > 0.75, nDCG@10 > 0.80

5.1.2 Recall@k

Definition: Fraction of relevant resources retrieved in top-k results.

Measurement:

- For each test query, identify all relevant resources in corpus (exhaustive or via expert judgment on random sample)
- $\text{Recall@k} = \frac{\# \text{ relevant in top-k}}{\text{total } \# \text{ relevant}}$
- **Baseline target:** Recall@10 > 0.70
- **Optimized target:** Recall@10 > 0.85

5.1.3 Coverage

Definition: Percentage of unique content chunks recommended across all queries.

Measurement:

- Log all recommended resources over 1 week
- $\text{Coverage} = \frac{\# \text{ unique chunks recommended}}{\text{total } \# \text{ chunks in corpus}}$
- **Target:** Coverage > 50% (avoid over-recommending popular content)

5.1.4 Time-to-First-Useful-Resource

Definition: Latency from query submission to first resource deemed useful by learner.

Measurement:

- Implicit: Time to first click + dwell time > 30 seconds
- Explicit: Thumbs-up on first resource
- **Target:** P50 < 5 seconds, P95 < 10 seconds

5.2 Minimality Metrics

5.2.1 Median Resource Length

Measurement:

- Videos: Median duration (seconds) of recommended segments
- PDFs: Median length (pages) of recommended segments
- **Target:** Videos < 90 seconds, PDFs < 1.5 pages

5.2.2 Overkill Rate

Definition: Percentage of recommendations exceeding target length thresholds.

Measurement:

- Set thresholds: Videos > 3 minutes, PDFs > 2 pages
- Overkill Rate = $\frac{\# \text{ recommendations over threshold}}{\text{total } \# \text{ recommendations}}$
- **Target:** Overkill Rate < 15%

5.2.3 Compression Ratio

Definition: Ratio of recommended segment length to full resource length.

Measurement:

- For each recommended segment, compute $\frac{\text{segment length}}{\text{full resource length}}$
- Average across all recommendations
- **Target:** Compression ratio < 0.3 (segments are < 30% of full resource)

5.3 Question Quality Metrics

5.3.1 Expert Rubric Scores

Rubric Dimensions:

1. **Clarity:** Is the question unambiguous and well-phrased? (1–5)
2. **Alignment:** Does it assess the intended concept/skill? (1–5)
3. **Bloom Level:** Does it match the target cognitive level? (1–5)
4. **Factuality:** Is it grounded in provided content? (1–5)

Measurement:

- Sample 100–200 generated questions per milestone
- 2–3 experts rate each question independently
- Aggregate: Mean score per dimension, overall score (average of 4 dimensions)
- **Target:** Overall score > 4.0 (good), > 4.5 (excellent)

5.3.2 Pass@k on Canonical Answers

Definition: Percentage of generated questions for which the canonical answer (from reference material) receives a passing grade.

Measurement:

- Generate questions from content with known answers
- Grade canonical answer using rubric grader
- $\text{Pass@k} = \frac{\# \text{ questions where canonical answer passes}}{\text{total } \# \text{ questions}}$
- **Target:** $\text{Pass@1} > 90\%$

5.3.3 Factuality via Reference-Grounded Checks

Method:

- NLI (Natural Language Inference) model: Check if question + answer entailed by source content
- Labels: Entailment (factual), Contradiction (hallucination), Neutral (unverifiable)
- **Target:** Entailment rate $> 95\%$, Contradiction rate $< 2\%$

Tools:

- Models: DeBERTa-v3-large-mnli, RoBERTa-large-mnli
- Thresholds: Entailment probability > 0.8 (confident), < 0.5 (reject question)

5.4 Assessment Quality Metrics

5.4.1 Item Discrimination (a)

Definition: Slope of the item characteristic curve; higher a means item better distinguishes high- from low-ability learners.

Measurement:

- Extract from IRT calibration: a parameter for each item
- **Target:** Median $a > 1.0$ (acceptable), > 1.5 (good), > 2.0 (excellent)
- **Flag:** Items with $a < 0.5$ (low discrimination) for review/retirement

5.4.2 Item Difficulty (b)

Definition: Ability level at which 50% probability of correct response.

Measurement:

- Extract from IRT: b parameter for each item
- **Target distribution:** $b \in [-2, 2]$ (covers range of abilities), roughly normal
- **Flag:** Items with $|b| > 3$ (extreme difficulty) for review

5.4.3 Guessing Parameter (c)

Definition: Lower asymptote of item characteristic curve; probability of correct response by random guessing.

Measurement:

- Extract from 3PL model: c parameter
- **Target:** For 4-option MCQ, $c \approx 0.20$ – 0.30 (slightly above chance)
- **Flag:** $c > 0.4$ (too easy to guess) or $c < 0.1$ (implausible)

5.4.4 Test Information and Ability Standard Error

Test Information: $I(\theta) = \sum_{i=1}^n I_i(\theta)$ where $I_i(\theta) = a_i^2 \cdot P_i(\theta) \cdot Q_i(\theta) / P_i'(\theta)^2$

Standard Error: $SE(\theta) = \frac{1}{\sqrt{I(\theta)}}$

Measurement:

- Compute for each learner after each test/session
- **Target:** $SE(\theta) < 0.4$ (acceptable precision), < 0.3 (good precision)
- Adaptive testing: Administer items near learner's θ to maximize information

5.4.5 Test-Retest Reliability

Definition: Correlation of θ estimates across two independent test administrations.

Measurement:

- Pilot: Administer parallel forms to 50–100 learners, 1 week apart
- Compute Pearson correlation: $\rho(\theta_{\text{test}}, \theta_{\text{retest}})$
- **Target:** $\rho > 0.80$ (acceptable), > 0.85 (good), > 0.90 (excellent)

5.5 Learning Outcome Metrics

5.5.1 $\Delta\theta$ Over Time

Definition: Change in ability estimate from session t to session $t + 1$.

Measurement:

- For each learner, compute $\Delta\theta_t = \theta_{t+1} - \theta_t$
- Aggregate: Mean $\Delta\theta$ across learners per week
- **Target:** Mean $\Delta\theta > 0.1$ per week (noticeable improvement)
- **Benchmark:** Compare to control group or historical baseline (if available)

5.5.2 Normalized Gain (Hake Gain)

Definition: $g = \frac{\theta_{\text{post}} - \theta_{\text{pre}}}{\theta_{\text{max}} - \theta_{\text{pre}}}$

Measurement:

- Pre-test: Assess θ_{pre} at start of course/unit
- Post-test: Assess θ_{post} at end
- θ_{max} : Theoretical maximum (e.g., 3 standard deviations above mean)
- **Interpretation:** $g < 0.3$ (low), $0.3 \leq g < 0.7$ (medium), $g \geq 0.7$ (high)
- **Target:** Mean $g > 0.4$ (medium gain)

5.5.3 Mastery Progression

Definition: Percentage of learners achieving target proficiency on each topic/skill.

Measurement:

- Define mastery threshold: $P(\text{correct}|\theta, b) > 0.70$ for items of target difficulty
- Compute: Mastery Rate = $\frac{\# \text{ learners above threshold}}{\text{total } \# \text{ learners}}$
- Track progression over time: Weekly mastery rate by topic
- **Target:** 70% mastery rate by end of unit

5.5.4 Downstream Task Performance

Definition: Performance on external assessments (e.g., final exams, standardized tests) after using the system.

Measurement:

- Compare: Users of adaptive system vs. control group (traditional instruction)
- Metrics: Mean score, pass rate, effect size (Cohen's d)
- **Target:** Effect size $d > 0.3$ (medium effect), ideally $d > 0.5$ (large effect)

5.6 Distinguishing Engagement from Learning

5.6.1 Engagement Metrics (Track but Do Not Optimize For)

- **Click-Through Rate (CTR):** % of recommended resources clicked
- **Dwell Time:** Average duration on resource (minutes)
- **Session Frequency:** # sessions per week
- **Completion Rate:** % of suggested activities completed

5.6.2 Learning Metrics (Primary Optimization Target)

- $\Delta\theta$: Ability growth per session/week
- **Quiz Accuracy Uplift**: Pre-resource vs. post-resource correctness
- **Mastery Rate**: % of topics at proficiency level
- **Downstream Performance**: External exam scores

5.6.3 Correlation Analysis

Method:

- Compute: $\rho(\text{engagement}, \Delta\theta)$ for each metric pair
- Scatter plots: Engagement (x-axis) vs. Learning (y-axis) per learner
- **Red flag**: High engagement + low $\Delta\theta$ (indicates ineffective content)
- **Green zone**: High engagement + high $\Delta\theta$ (effective and engaging)

Action:

- If $\rho < 0.3$: Engagement is decoupled from learning \rightarrow audit content quality
- If negative correlation: Engaging content may be distracting \rightarrow investigate

5.7 Safety & Accuracy Metrics

5.7.1 Hallucination Rate

Definition: Percentage of LLM outputs that contradict or are unsupported by retrieved content.

Measurement:

- Sample 200–500 generated questions/explanations per milestone
- NLI check: Entailment with source content
- Expert review: 10% random sample for factual errors
- Hallucination Rate = $\frac{\# \text{ contradictions or unsupported claims}}{\text{total } \# \text{ outputs}}$
- **Target:** Hallucination rate $< 3\%$

5.7.2 Refusal/Deferral Accuracy

Definition: Correctness of system’s decision to refuse or defer to human when uncertain.

Measurement:

- Test set: 100 in-scope queries + 50 out-of-scope queries
- Metrics: Precision (true refusals / all refusals), Recall (true refusals / should-refuse cases)
- **Target:** Precision > 0.90 , Recall > 0.85

5.8 Evaluation Protocol per Milestone

Milestone	Metrics to Evaluate	Acceptance Criteria
M1 (RAG Base-line)	nDCG@5, Recall@10, Median length, Overkill rate	nDCG@5 > 0.6, Recall@10 > 0.70, Median < 90s, Overkill < 20%
M2 (Reranking + Segmentation)	nDCG@5, Compression ratio, Time-to-first	nDCG@5 > 0.70, Compression < 0.3, Time < 6s (P95)
M3 (Pedagogy v1)	Expert rubric score, Pass@1, Hallucination rate	Overall score > 4.0, Pass@1 > 85%, Hallucination < 5%
M4 (Bandits)	$\Delta\theta$, Normalized gain, Bandit regret	Mean $\Delta\theta$ > 0.08/week, g > 0.35, Regret decreasing
M5 (LoRA FT)	Expert rubric score, Grading consistency, $\Delta\theta$	Overall score > 4.3, κ > 0.85, $\Delta\theta$ > 0.10/week
M6 (Production)	All above + Safety metrics, P95 latency, Cost/learner	Hallucination < 3%, Refusal precision > 0.90, Latency < 10s, Cost < \$0.50/session

Table 3: Milestone Evaluation Criteria

6 Stepwise Roadmap (12 Weeks)

6.1 Milestone 1 (Weeks 1–2): RAG Baseline with Minimality Constraints

6.1.1 Objectives

- Deploy functional RAG system with hybrid retrieval (BM25 + dense embeddings)
- Enforce hard caps on resource length (videos ≤ 3 min, PDFs ≤ 2 pages)
- Achieve baseline retrieval quality (nDCG@5 > 0.6 , Recall@10 > 0.70)
- Establish evaluation harness and red-team test cases

6.1.2 Tasks

1. Content Ingestion:

- Parse videos (ASR via Whisper), PDFs (PyMuPDF)
- Chunk by semantic boundaries (30–180s for video, paragraphs for PDF)
- Extract metadata (title, topic, duration/length, keywords)

2. Embedding & Indexing:

- Embed chunks using OpenAI `text-embedding-3-large`
- Store in vector DB (Pinecone or Weaviate)
- Build BM25 index (Elasticsearch or custom)

3. Hybrid Retrieval:

- Implement RRF fusion (0.3 BM25 + 0.7 dense)
- Retrieve top-50 from each, fuse to top-20

4. Minimality Filtering:

- Hard filter: Remove chunks > 3 min (video) or > 2 pages (PDF)
- Rank by: Semantic similarity / duration (or pages)
- Return top-3 to user

5. Evaluation Harness:

- Collect 200–300 test queries (diverse topics, complexities)
- Expert labeling: Relevance ratings for top-10 results
- Compute: nDCG@5, nDCG@10, Recall@10, median length, overkill rate

6. Red-Team Test Cases:

- Adversarial queries: Ambiguous, out-of-scope, edge cases
- Test refusal logic (placeholder: "I don't have information on that")
- Document failure modes

6.1.3 Deliverables

- Functional RAG API: `POST /retrieve` (query \rightarrow top-3 resources)
- Evaluation report: Metrics table, example retrievals, failure analysis
- Jupyter notebook: Reproducible eval pipeline
- Data card: Content corpus stats (# videos, PDFs, total duration/pages)

6.1.4 Acceptance Criteria

- $\text{nDCG@5} > 0.6$, $\text{Recall@10} > 0.70$
- Median resource length < 90 seconds (videos), < 1.5 pages (PDFs)
- Overkill rate $< 20\%$
- P95 latency < 8 seconds

6.2 Milestone 2 (Weeks 3–4): Cross-Encoder Reranking & Video/PDF Segmentation

6.2.1 Objectives

- Improve retrieval precision with cross-encoder reranker
- Implement video segmentation (ASR + scene detection) and PDF section extraction
- Generate JSON-structured outputs for downstream consumption
- Achieve $\text{nDCG@5} > 0.70$, compression ratio < 0.3

6.2.2 Tasks

1. Cross-Encoder Reranking:

- Deploy `ms-marco-MiniLM-L-12-v2` (self-hosted or HuggingFace Inference API)
- Input: Top-20 candidates from M1 retrieval
- Output: Reranked top-5 by relevance score

2. Video Segmentation:

- ASR: Integrate Whisper API (or self-host Whisper-large-v3)
- Scene detection: `PySceneDetect` on video files
- Merge: Align ASR sentence boundaries with scene changes
- Extract: 30–180s clips with timestamps

3. PDF Section Detection:

- Parse: Identify headers (font size, formatting)
- Segment: 0.5–2 page chunks preserving section context
- Extract: Include images/figures with captions

4. Sufficiency Scoring:

- For each segment, compute: $\frac{\text{similarity}(q,s)}{\text{duration}/\text{pages}(s)}$
- LLM clarity check (optional few-shot prompt): "Rate pedagogical clarity 0–10"
- Select top-1 segment with highest sufficiency score

5. JSON Output Schema:

- Schema: `{query, resources: [{id, title, type, url, timestamp/page_range, duration/length, relevance_score, sufficiency_score}]}`
- Validate: JSON schema validator (Pydantic or jsonschema)

6. MMR Diversification:

- Apply MMR ($\lambda = 0.7$) to top-5 reranked results
- Return top-3 diverse segments

6.2.3 Deliverables

- Enhanced API: `POST /retrieve_v2` with reranking + segmentation
- Video processing pipeline: ASR + scene detection + segmenter
- PDF processing pipeline: Section extractor
- Evaluation report: nDCG@5 (improved), compression ratio, segment examples
- Model card: Cross-encoder specs, performance, latency

6.2.4 Acceptance Criteria

- nDCG@5 > 0.70 (10% improvement over M1)
- Compression ratio < 0.3 (segments are < 30% of full resources)
- P95 latency < 6 seconds (including segmentation)
- No malformed JSON outputs (100% schema compliance)

6.3 Milestone 3 (Weeks 5–6): Pedagogy Tools v1

6.3.1 Objectives

- Deploy prompt-based question generator aligned to Bloom levels
- Implement rubric-based grader with chain-of-thought reasoning
- Add hint generator for scaffolding
- Achieve expert approval > 80% for generated questions

6.3.2 Tasks

1. Question Generation:

- Prompt design: Few-shot examples (10–20 exemplars per Bloom level)
- Input: Resource content + desired Bloom level (Remember/Understand/Apply/Analyze)
- Output: {question, answer_key, distractors (if MCQ), bloom_level}
- Answerability check: LLM self-critique ("Can this be answered from resource?")

2. Rubric-Based Grading:

- Rubric template: 4 levels (Novice, Developing, Proficient, Advanced) with explicit criteria
- Prompt: Chain-of-thought with rubric + reference answer + student response
- Output: {level, score, rationale, confidence}
- Confidence threshold: Defer to human if confidence < 0.7

3. Hint Generation:

- Progressive hints: (1) Conceptual ("Think about X"), (2) Procedural ("Try Y approach"), (3) Partial solution
- Trigger: After 1–2 incorrect attempts or explicit request
- Output: {hint_level, hint_text}

4. Worked Examples:

- Generate: Step-by-step solution to similar problem
- Annotate: Explain each step's rationale
- Deliver: After learner completes (or struggles with) question

5. Validation:

- Sample 200 generated questions
- Expert review: Clarity, alignment, Bloom level, factuality (1–5 scale per dimension)
- Factuality check: NLI model (DeBERTa-mnli) for grounding

6.3.3 Deliverables

- Pedagogy API: POST /generate_question, POST /grade_response, POST /get_hint
- Prompt library: Versioned few-shot exemplars for each tool
- Evaluation report: Expert rubric scores, Pass@1, hallucination rate
- Example outputs: 50 question/grade/hint triplets with expert annotations

6.3.4 Acceptance Criteria

- Overall expert rubric score > 4.0 (out of 5)
- Pass@1 on canonical answers $> 85\%$
- Hallucination rate $< 5\%$ (via NLI + expert review)
- Grading consistency: $\kappa > 0.75$ (agreement with human raters on 100 test cases)

6.4 Milestone 4 (Weeks 7–8): Bandit/RLHF for Content Selection

6.4.1 Objectives

- Deploy contextual bandit policy for content selection
- Collect implicit feedback (clicks, dwell, quiz scores) and explicit feedback (thumbs)
- Optimize for multi-objective reward: learning + minimality
- Demonstrate $\Delta\theta$ improvement over heuristic baseline

6.4.2 Tasks

1. Bandit Infrastructure:

- Policy server: Thompson Sampling with Beta priors (initial)
- Context: $x = [\theta, \text{query_embedding}, \text{resource_metadata}]$
- Actions: Select from top-5 reranked candidates (from M2)
- Exploration rate: 20% (uniform random)

2. Reward Function:

- $R = 1.0 \cdot \Delta\theta + 0.3 \cdot \text{brevity_bonus} - 0.5 \cdot \text{irrelevance_penalty} - 0.1 \cdot \text{latency_cost}$
- $\Delta\theta$ proxy: Quiz correctness post-resource (short-term)
- Brevity: $\max(0, \frac{180 - \text{duration}}{180})$ for videos
- Irrelevance: $1 - \text{cosine}(\text{resource}, \text{query})$
- Latency: Normalized response time

3. Logging & Feedback:

- Log: (timestamp, learner_id, query, context, action, reward, propensity)
- Storage: Kafka \rightarrow Data warehouse (BigQuery or Snowflake)
- Volume target: 10k–50k interactions in Weeks 7–8

4. Policy Training:

- Week 7: Collect data under heuristic policy (cold-start)
- Week 8: Train bandit on logged data, deploy with exploration=20%
- Off-policy eval: IPS/DR estimators to predict performance before deployment

5. IRT Ability Tracking:

- Implement: EAP estimation for θ after each quiz
- Calibrate: Initial item parameters from M3 question difficulty estimates
- Update: Recalibrate parameters weekly using cumulative response data

6. A/B Test:

- Control (50%): Heuristic policy from M2
- Treatment (50%): Bandit policy
- Metrics: $\Delta\theta$, normalized gain, minimality, user satisfaction
- Duration: 2 weeks (Weeks 7–8)

6.4.3 Deliverables

- Bandit service: API for policy inference + logging
- IRT module: Ability estimation + item calibration
- A/B test report: Comparison of control vs. treatment on all metrics
- Decision memo: Proceed to LoRA fine-tuning (M5) if $\Delta\theta$ improves by $\geq 10\%$
- Telemetry dashboard: Real-time bandit diagnostics (exploration rate, reward trends, regret)

6.4.4 Acceptance Criteria

- Mean $\Delta\theta$ per week > 0.08 (treatment group)
- Normalized gain $g > 0.35$ (medium Hake gain)
- Bandit policy outperforms heuristic by $\geq 10\%$ on $\Delta\theta$
- Median resource length stable or reduced (< 90 seconds)
- Off-policy evaluation: Predicted reward matches actual reward within 10% (model calibration check)

6.5 Milestone 5 (Weeks 9–10): Optional LoRA Fine-Tuning & A/B Test**6.5.1 Objectives**

- Fine-tune task-specific LoRA adapters for pedagogy tasks
- Compare fine-tuned vs. prompt-only versions via A/B test
- Achieve expert approval $> 85\%$ and grading consistency $\kappa > 0.85$
- Decision gate: Proceed only if fine-tuning shows measurable gains

6.5.2 Tasks

1. Training Data Preparation:

- Question generation: 500–2k exemplars from M3 expert-reviewed + historical Q&A logs
- Rubric grading: 1k–2k graded responses with rubric levels + rationale
- Distractor generation: 300–500 MCQs with plausible distractors + quality ratings
- Pedagogical style: 200–500 hint/explanation exemplars

2. LoRA Fine-Tuning:

- Base model: Llama 3.1 70B or Mistral Large (or GPT-4o if API supports adapters)
- LoRA config: $r = 16$, $\alpha = 32$, target modules: query/value projections
- Training: 2–4 epochs, learning rate $1e - 4$, batch size 8 (gradient accumulation)
- Infrastructure: 2x A100 GPUs, 4–12 hours per adapter

3. Adapter Modules:

- Adapter 1: Question generator (input: content + Bloom level \rightarrow output: question + answer)
- Adapter 2: Rubric grader (input: question + rubric + response \rightarrow output: level + rationale)
- Adapter 3: Distractor generator (input: question + answer \rightarrow output: 3 distractors)
- Adapter 4: Pedagogical explainer (input: question + learner error \rightarrow output: hint/explanation)

4. A/B Test:

- Control (50%): Prompt-only pedagogy tools (M3)
- Treatment (50%): LoRA-adapted pedagogy tools
- Metrics: Expert rubric scores, grading consistency, $\Delta\theta$, learner feedback
- Duration: 2 weeks (Weeks 9–10)

5. Validation:

- Question quality: Sample 200 generated questions, expert review
- Grading consistency: 100 responses graded by adapter vs. human raters, compute κ
- Distractor quality: Pilot 50 MCQs with learners, measure distractor selection rates

6.5.3 Deliverables

- LoRA adapters: 4 trained adapters + model cards (architecture, training data, hyperparameters)
- Inference pipeline: vLLM or Lorax for efficient adapter serving
- A/B test report: Comparison of prompt-only vs. LoRA-adapted on all metrics
- Decision memo: Adopt LoRA if improvement $\geq 5\%$ on expert scores and $\Delta\theta$; otherwise, revert to prompt-only
- Migration plan: Procedure for upgrading base model while preserving adapters (transfer learning)

6.5.4 Acceptance Criteria

- Overall expert rubric score > 4.3 (5% improvement over M3)
- Grading consistency $\kappa > 0.85$ (10% improvement over M3)
- Mean $\Delta\theta$ per week > 0.10 (5% improvement over M4)
- Cost-benefit: Inference cost increase $< 20\%$ vs. prompt-only (due to adapter overhead)
- Decision: If criteria met, proceed to production with LoRA; if not, revert to prompt-only

6.6 Milestone 6 (Weeks 11–12): Production Hardening

6.6.1 Objectives

- Implement comprehensive guardrails (hallucination detection, refusal logic, safety filters)
- Deploy bias checks and compliance audits (GDPR, FERPA, accessibility)
- Set up telemetry dashboards for monitoring and alerting
- Achieve production-ready SLAs: hallucination $< 3\%$, P95 latency $< 10s$, cost $< \$0.50/\text{session}$

6.6.2 Tasks

1. Hallucination Detection:

- Retrieval-grounded verification: All LLM outputs cite source chunks
- NLI-based fact-checking: DeBERTa-mnli checks entailment with sources
- Contradiction detector: Flag if output contradicts source material
- Threshold: Reject outputs with entailment probability < 0.8

2. Refusal Logic:

- Intent classifier: Detect out-of-scope queries (off-topic, harmful, non-educational)
- Confidence threshold: Refuse if retrieval confidence < 0.5 or ambiguous query
- Polite refusal templates: "I can help with [topics]. Your question about [X] is outside my scope."
- Escalation: Option to connect with human tutor if available

3. Safety Filters:

- Content moderation: OpenAI Moderation API or Perspective API for toxic content
- PII redaction: Detect and anonymize names, emails, phone numbers in logs
- Bias checks: Audit question generation for demographic bias (gender, race, age stereotypes)

4. Compliance:

- GDPR: Right to erasure (delete learner data on request), data minimization, consent flows

- FERPA: Student data privacy (no sharing without consent), role-based access controls
- Accessibility: WCAG 2.1 AA compliance (screen reader support, keyboard navigation, alt text)

5. Telemetry Dashboards:

- Metrics: Retrieval nDCG, minimality, question quality, $\Delta\theta$, hallucination rate, P95 latency, cost/session
- Alerts: θ SE > 0.5, item drift > 0.2, hallucination > 5%, latency > 15s
- Tools: Grafana + Prometheus (or Datadog, New Relic)

6. Educator Dashboard:

- Class-level: Average θ , $\Delta\theta$, mastery rates, struggling learners
- Individual drill-down: Trajectory, topic proficiency, intervention recommendations
- Content analytics: Most/least effective resources (by $\Delta\theta$)

7. Learner Explanations:

- "Why this resource?": Explain selection rationale (relevance, length, difficulty match)
- "Why this question?": Explain pedagogical intent (skill assessed, Bloom level)
- "What's next?": Suggest next topic/skill based on current mastery

8. Load Testing:

- Simulate: 10k concurrent users, 50k requests/hour
- Metrics: P95/P99 latency, error rate, resource utilization
- Auto-scaling: Configure Kubernetes HPA or cloud auto-scaling policies

9. Disaster Recovery:

- Backups: Daily snapshots of vector DB, data warehouse
- Failover: Multi-region deployment (primary + backup)
- Incident response: Runbooks for common failures (API outage, DB corruption, hallucination spike)

6.6.3 Deliverables

- Production deployment: Fully instrumented system with guardrails + monitoring
- Compliance report: GDPR/FERPA audit + accessibility checklist
- Runbooks: Incident response procedures for common issues
- Telemetry dashboard: Public URL for stakeholders (view-only access)
- User documentation: Educator guide + learner guide (how to use system, interpret explanations)
- Launch readiness review: Sign-off from security, legal, and product teams

6.6.4 Acceptance Criteria

- Hallucination rate $< 3\%$ (500 sample outputs audited)
- Refusal precision > 0.90 , recall > 0.85 (100 test cases)
- P95 latency < 10 seconds (under 10k concurrent users)
- Cost per session $< \$0.50$ (including all APIs, compute, storage)
- Compliance: 100% pass on GDPR/FERPA checklist
- Accessibility: WCAG 2.1 AA compliance (automated + manual audit)
- Uptime: 99.5% availability (4 hours downtime/month acceptable for pilot)

6.7 Roadmap Summary Table

Milestone	Duration	Key Tasks	Deliverables	Acceptance Criteria
M1	Weeks 1–2	RAG baseline, minimality constraints, eval harness, red-team	API, eval report, notebook, data card	nDCG@5 > 0.6 , Recall@10 > 0.70 , Median $< 90s$
M2	Weeks 3–4	Cross-encoder reranking, video/PDF segmentation, JSON outputs, MMR	Enhanced API, video/PDF pipelines, model card	nDCG@5 > 0.70 , Compression < 0.3 , Latency $< 6s$
M3	Weeks 5–6	Question generation, rubric grading, hints, answerability checks	Pedagogy APIs, prompt library, eval report	Expert score > 4.0 , Pass@1 $> 85\%$, Hallucination $< 5\%$
M4	Weeks 7–8	Contextual bandits, IRT tracking, reward function, A/B test	Bandit service, IRT module, A/B report, telemetry	$\Delta\theta > 0.08/\text{week}$, $g > 0.35$, 10% improvement
M5	Weeks 9–10	LoRA fine-tuning (4 adapters), A/B test, validation	Adapters, inference pipeline, A/B report, migration plan	Expert score > 4.3 , $\kappa > 0.85$, $\Delta\theta > 0.10/\text{week}$
M6	Weeks 11–12	Guardrails, safety, compliance, telemetry, educator/learner dashboards	Production system, compliance report, runbooks, docs	Hallucination $< 3\%$, Latency $< 10s$, Cost $< \$0.50/\text{session}$

Table 4: 12-Week Roadmap Summary

7 Reinforcement Learning Design

7.1 Problem Formulation

Objective: Learn a policy $\pi(a|x)$ that selects content (action a) given context (x) to maximize long-term learning outcomes (reward R) under minimality and accuracy constraints.

Why RL/Bandits:

- **Exploration-exploitation tradeoff:** Discover which resources work best for different learners while exploiting known good content.
- **Delayed rewards:** Learning happens over multiple sessions; need credit assignment.
- **Personalization:** Different learners have different θ , preferences, learning styles.
- **Distribution shift:** Content corpus evolves, learner population changes over time.

7.2 Multi-Objective Reward Function

Reward Definition:

$$R = w_1 \cdot \Delta\theta + w_2 \cdot B(d) - w_3 \cdot I(q, r) - w_4 \cdot L(t)$$

Component 1: Learning Gain ($\Delta\theta$)

- **Primary signal:** Change in IRT ability estimate after interaction.
- **Computation:** $\Delta\theta = \theta_{\text{post}} - \theta_{\text{pre}}$
- **Proxy (short-term):** Quiz correctness post-resource: $\frac{\# \text{ correct}}{\text{total } \# \text{ questions}}$
- **Ground truth (long-term):** $\Delta\theta$ over 1 week from pre/post-tests.
- **Normalization:** Scale to $[0, 1]$, typical range $\Delta\theta \in [0, 0.5]$ per session.
- **Weight:** $w_1 = 1.0$ (highest priority).

Component 2: Minimality Bonus ($B(d)$)

- **Intent:** Reward shorter resources that still enable learning.
- **Computation:** $B(d) = \max\left(0, \frac{T_{\text{target}} - d}{T_{\text{target}}}\right)$
- Where $T_{\text{target}} = 90$ seconds (videos) or 1 page (PDFs), d = actual duration/length.
- **Range:** $B \in [0, 1]$, where $B = 1$ if $d = 0$ (shortest), $B = 0$ if $d \geq T_{\text{target}}$.
- **Weight:** $w_2 = 0.3$ (encourage brevity but don't sacrifice learning).

Component 3: Irrelevance Penalty ($I(q, r)$)

- **Intent:** Penalize resources with low semantic alignment to query.
- **Computation:** $I(q, r) = 1 - \text{cosine}(\text{embed}(q), \text{embed}(r))$
- **Range:** $I \in [0, 1]$, where $I = 0$ (perfectly aligned), $I = 1$ (orthogonal).

- **Weight:** $w_3 = 0.5$ (penalize off-topic content).

Component 4: Latency Cost ($L(t)$)

- **Intent:** Penalize slow responses (UX penalty).
- **Computation:** $L(t) = \frac{t}{10 \text{ seconds}}$ where t = response time.
- **Range:** $L \in [0, \infty)$, typical range $[0.3, 1.5]$.
- **Weight:** $w_4 = 0.1$ (minor penalty, prioritize learning over speed).

Weight Tuning:

- **Initial weights:** $w_1 = 1.0$, $w_2 = 0.3$, $w_3 = 0.5$, $w_4 = 0.1$
- **Tuning method:** Pareto frontier analysis (multi-objective optimization)
- Vary weights, plot tradeoff curves: $\Delta\theta$ vs. minimality, learning vs. relevance
- **Stakeholder input:** Educators prioritize learning (w_1 high), product team balances UX (w_2, w_4)

7.3 Contextual Bandit Approach

7.3.1 Algorithm Choice

Phase 1 (Weeks 1–4): Thompson Sampling

- **Model:** Beta-Bernoulli bandit (for binary rewards) or Gaussian bandit (for continuous rewards)
- **Prior:** Beta(1, 1) or Gaussian($\mu = 0$, $\sigma^2 = 1$) for each action
- **Update:** Posterior update after each interaction (Bayesian inference)
- **Selection:** Sample from posterior, select action with highest sampled reward
- **Exploration:** Automatic via posterior sampling (high uncertainty \rightarrow more exploration)

Phase 2 (Weeks 5–8): LinUCB (Linear Upper Confidence Bound)

- **Model:** Assume reward is linear in context features: $R(x, a) = x^T \theta_a + \epsilon$
- **Features:** $x = [\theta_{\text{learner}}, \text{query_emb}, \text{resource_meta}]$, dimension $d \approx 50\text{--}100$
- **Update:** Ridge regression update for θ_a after each interaction
- **Selection:** $a^* = \arg \max_a \left(x^T \hat{\theta}_a + \alpha \sqrt{x^T A_a^{-1} x} \right)$
- Where A_a is the design matrix for action a , α is exploration parameter (typically 0.1–1.0)
- **Advantage:** Fast convergence, interpretable, proven regret bounds ($O(\sqrt{dT \log T})$)

Phase 3 (Weeks 9+): Neural Bandit (Optional)

- **Model:** Neural network to predict $R(x, a)$ from context-action pairs

- **Architecture:** 2–3 layer MLP, 128–256 hidden units
- **Exploration:** Ensemble disagreement or dropout-based uncertainty
- **Update:** Mini-batch gradient descent on logged data every day/week
- **Advantage:** Captures nonlinear relationships, but needs more data and compute

7.3.2 Off-Policy Evaluation

Challenge: Can't A/B test every policy change; need to evaluate new policies offline.

Method 1: Inverse Propensity Scoring (IPS)

- **Estimator:** $\hat{V}(\pi) = \frac{1}{n} \sum_{i=1}^n \frac{\pi(a_i|x_i)}{\pi_0(a_i|x_i)} r_i$
- Where π_0 is the logging policy (historical), π is the new policy to evaluate.
- **Advantage:** Unbiased under correct propensity estimates.
- **Disadvantage:** High variance if propensities are small (divide by near-zero).

Method 2: Doubly Robust (DR)

- **Estimator:** $\hat{V}(\pi) = \frac{1}{n} \sum_{i=1}^n \left[\frac{\pi(a_i|x_i)}{\pi_0(a_i|x_i)} (r_i - \hat{r}(x_i, a_i)) + \sum_a \pi(a|x_i) \hat{r}(x_i, a) \right]$
- Where $\hat{r}(x, a)$ is a learned reward model (e.g., from LinUCB or neural net).
- **Advantage:** Lower variance than IPS, still unbiased if either propensity or reward model is correct.
- **Use case:** Preferred for pre-deployment evaluation.

Method 3: Simulator

- **Approach:** Replay historical logged data under new policy.
- For each historical interaction (x_i, a_i, r_i) , check if new policy would select a_i .
- If yes, count r_i toward cumulative reward; if no, skip.
- **Caveat:** Underestimates true reward (only counts on-policy data), but useful for what-if analysis.

7.3.3 Safety Constraints

Challenge: Prevent policy from over-optimizing reward at expense of safety (e.g., always selecting shortest resource even if it doesn't teach).

Constraint 1: Minimum Exploration

- **Rule:** With probability $\epsilon = 0.10$, select uniformly random action (ignore policy).
- **Rationale:** Ensures continued discovery of new content, prevents premature convergence.

Constraint 2: Blacklist

- **Rule:** If resource receives consistent negative feedback (thumbs-down > 30% or $\Delta\theta < 0$), exclude from action space for 1 week.
- **Rationale:** Protects learners from known-bad content.

Constraint 3: Per-Resource Quotas

- **Rule:** Limit each resource to < 10% of total recommendations per week.
- **Rationale:** Prevents policy from overfitting to a few popular resources, maintains diversity.

Constraint 4: Teacher Override

- **Rule:** During pilot (Weeks 7–10), educators can flag policy decisions for review.
- **Process:** Flagged cases go to weekly review meeting, update blacklist or adjust reward weights if needed.

7.4 Escalation to Full RL

When to Escalate:

- **Bandit plateau:** If LinUCB performance stops improving after 50k+ interactions.
- **Long-horizon rewards:** If learning gains manifest over multiple sessions (need credit assignment).
- **Sequential decision-making:** If we want to optimize entire learning trajectory (not just single resource).

Full RL Approach:

- **MDP Formulation:**
 - State: $s = [\theta, \text{mastery_map}, \text{recent_history}, \text{current_query}]$
 - Action: $a = \text{resource_id}$
 - Reward: Same multi-objective reward as above
 - Transition: Deterministic (state updates based on learner response)
- **Algorithm:** Offline RL (BCQ, CQL, IQL) trained on logged data.
- **Advantage:** Can optimize long-term learning trajectory (e.g., skill prerequisites, spaced repetition).
- **Requirements:** $\geq 100\text{k}$ logged interactions, simulator for policy testing, safety constraints (same as bandits).

Decision Gate (Week 12):

- **Escalate to RL if:** Bandit shows < 5% improvement after 50k interactions AND we have sufficient logged data.
- **Stay with bandits if:** Bandit continues improving OR data volume insufficient (< 50k interactions).

7.5 Practical Implementation Checklist

1. **Data collection:** Log (timestamp, learner_id, context, action, reward, propensity) for every interaction.
2. **Feature engineering:** Encode context (θ , query_emb, resource_meta) as fixed-dimension vector.
3. **Cold-start:** Week 1–4 use uniform random or heuristic policy to collect initial data.
4. **Policy training:** Week 5–8 train LinUCB on logged data, deploy with $\epsilon = 0.20$ exploration.
5. **Off-policy eval:** Before each deployment, run IPS/DR to estimate new policy value.
6. **A/B test:** Deploy new policy to 50% of users, compare against control (heuristic or previous policy).
7. **Monitoring:** Track exploration rate, reward trends, regret bounds, safety violations.
8. **Retraining cadence:** Retrain policy weekly (early) \rightarrow monthly (mature) with cumulative data.
9. **Safety checks:** Review blacklist, check for diversity violations, educator feedback loop.
10. **Escalation trigger:** If bandit plateaus, consider offline RL (requires 100k+ interactions + simulator).

8 Fine-Tuning Policy

8.1 General Principle: Avoid Premature Fine-Tuning

Rationale:

- Prompt engineering + RAG is fast, flexible, and works well for most tasks.
- Fine-tuning locks us into specific model versions, requires retraining for upgrades.
- Foundation models improve rapidly; fine-tuning today may be obsolete in 6 months.
- LoRA/PEFT provides middle ground: task-specific adaptation with upgrade agility.

Decision Rule: Fine-tune ONLY if:

1. Prompt engineering has plateaued (no improvement after multiple prompt iterations).
2. We have ≥ 500 –2k high-quality labeled examples for the task.
3. Task-specific fine-tuning shows $\geq 5\%$ improvement on key metrics in offline eval.
4. Inference cost/latency is acceptable (fine-tuned models can be faster/cheaper if self-hosted).

8.2 When to Fine-Tune

8.2.1 Task 1: Question Generation

Entry Criteria:

- Prompt-only expert approval $< 80\%$ (quality plateau).
- We have ≥ 500 –2k exemplars: (content, Bloom_level, question, answer, distractors).
- Sources: Historical Q&A logs + M3 expert-reviewed questions + synthetic augmentation.

Fine-Tuning Approach:

- Base model: Llama 3.1 8B or Mistral 7B (smaller models sufficient for this task).
- LoRA config: $r = 16$, $\alpha = 32$, target modules: `q_proj`, `v_proj`.
- Training: 2–4 epochs, learning rate $1e-4$, batch size 8.
- Validation: Hold out 20% of exemplars, track perplexity + expert approval on validation set.

Expected Improvement:

- Expert approval: 80% (prompt-only) \rightarrow 88–92% (LoRA).
- Consistency: Reduced variance in question quality across topics.
- Inference: Slightly faster (no need for long few-shot examples in prompt).

8.2.2 Task 2: Rubric-Based Grading

Entry Criteria:

- Grading consistency (Krippendorff's α) < 0.80 with prompt-only.
- We have $\geq 1\text{k}$ – 2k graded responses: (question, rubric, student_response, level, rationale).
- Sources: Historical graded assignments + M3 expert-labeled test cases.

Fine-Tuning Approach:

- Base model: Llama 3.1 13B or GPT-4o (if API supports adapters).
- LoRA config: $r = 16$, $\alpha = 32$, target modules: `q_proj`, `v_proj`.
- Training: 3–5 epochs, learning rate $5e - 5$, batch size 4.
- Validation: Inter-rater agreement (α) on holdout set.

Expected Improvement:

- Grading consistency: 0.75–0.80 (prompt-only) \rightarrow 0.85–0.90 (LoRA).
- Rationale quality: More detailed, pedagogically grounded feedback.
- Confidence calibration: Better alignment between confidence scores and actual correctness.

8.2.3 Task 3: Distractor Generation (MCQ)

Entry Criteria:

- Distractor quality: $< 70\%$ rated as plausible by educators.
- We have ≥ 300 – 500 MCQs with high-quality distractors + quality ratings.
- Sources: Historical assessment database + expert-curated MCQs.

Fine-Tuning Approach:

- Base model: Llama 3.1 8B or Mistral 7B.
- LoRA config: $r = 8$, $\alpha = 16$ (smaller adapter for simpler task).
- Training: 2–3 epochs, learning rate $1e - 4$, batch size 8.
- Validation: Distractor plausibility (expert ratings), selection rates (pilot with learners).

Expected Improvement:

- Plausibility: 65–70% (prompt-only) \rightarrow 80–85% (LoRA).
- Selection rates: More uniform distribution (good distractors attract learners with misconceptions).

8.2.4 Task 4: Pedagogical Explainer (Hints, Worked Examples)

Entry Criteria:

- Hint quality: $< 75\%$ rated as helpful by learners.
- We have ≥ 200 –500 exemplars: (question, learner_error, hint, worked_example).
- Sources: Expert-written hints + scaffolding templates.

Fine-Tuning Approach:

- Base model: Llama 3.1 13B (larger model for nuanced pedagogy).
- LoRA config: $r = 16$, $\alpha = 32$, target modules: `q_proj`, `v_proj`.
- Training: 2–4 epochs, learning rate $5e - 5$, batch size 4.
- Validation: Learner feedback (helpfulness ratings), $\Delta\theta$ after hint.

Expected Improvement:

- Helpfulness: 72–75% (prompt-only) \rightarrow 85–88% (LoRA).
- Scaffolding quality: More tailored to learner’s specific error pattern.

8.3 LoRA/PEFT Configuration

Advantages of LoRA:

- **Parameter efficiency:** Train only 0.1–1% of model parameters (adapters).
- **Upgrade agility:** When base model updates, retrain adapters (much faster than full FT).
- **Multi-task serving:** Load different adapters for different tasks (vLLM, Lorax).
- **Lower cost:** Training takes hours (not days) on 1–2 GPUs.

Typical LoRA Hyperparameters:

- **Rank (r):** 8–16 for simple tasks, 16–32 for complex tasks.
- **Alpha (α):** $2r$ (scaling factor for adapter weights).
- **Target modules:** `q_proj`, `v_proj` (query and value projections in attention layers).
- **Dropout:** 0.05–0.1 (regularization to prevent overfitting).

Training Infrastructure:

- **GPUs:** 1–2x A100 (40GB or 80GB) for 7B–13B models, 2–4x A100 for 70B models.
- **Framework:** HuggingFace PEFT, Unsloth, or Axolotl.
- **Training time:** 4–12 hours per adapter (depending on dataset size and model size).
- **Cost:** \$50–\$200 per training run on cloud (AWS, GCP, Azure).

Inference Infrastructure:

- **Serving:** vLLM (with LoRA support) or Lorax (multi-adapter serving).
- **Adapter swapping:** Load different adapters for different tasks (e.g., question gen vs. grading).
- **Latency:** Adapter adds $< 50\text{ms}$ vs. base model inference.

8.4 Migration Plan for Model Upgrades

Challenge: Base models upgrade frequently (e.g., GPT-4o \rightarrow GPT-4.5, Llama 3.1 \rightarrow Llama 4). How to preserve adapter investment?

Strategy 1: Adapter Transfer Learning

1. When new base model released, evaluate prompt-only performance on validation set.
2. If new base model $> 5\%$ better, consider migration.
3. Retrain adapters on new base model (faster than training from scratch, can reuse datasets).
4. A/B test: Old base + adapters vs. New base + retrained adapters.
5. Migrate if new base outperforms old by $\geq 3\%$ on key metrics.

Strategy 2: Adapter Ensembles (Optional)

- Run both old and new base models in parallel for 1–2 weeks.
- Route queries to each model 50/50, compare outputs.
- Gradually increase traffic to new model if performance is better.
- Decommission old model once new model proves stable.

Strategy 3: Gradual Rollout

- Week 1: 10% of traffic to new model (canary deployment).
- Week 2: 25% of traffic if no regressions.
- Week 3: 50% of traffic.
- Week 4: 100% of traffic, decommission old model.

Versioning:

- Track: (base_model_version, adapter_version, training_date, performance_metrics).
- Rollback plan: If new model underperforms, revert to previous version within 1 hour.

8.5 Decision Checklist for Fine-Tuning

Criterion		Threshold	Assessment Method
Prompt-only plateau	performance	< 80% on key metric	Offline eval on validation set
High-quality labeled data available		≥ 500–2k exemplars	Data audit, inter-rater agreement check
Expected improvement		≥ 5% on key metric	Offline eval of fine-tuned model
Inference cost acceptable		< 20% increase vs. prompt-only	Benchmarking (tokens/sec, latency)
Upgrade agility preserved		Can retrain in < 1 week	LoRA/PEFT architecture (not full FT)
Team capacity		Can manage training pipeline	ML engineering availability

Table 5: Fine-Tuning Decision Checklist

Decision Rule:

- If ALL criteria met: Proceed with LoRA fine-tuning.
- If ANY criterion fails: Stick with prompt engineering, revisit in 3 months.

9 Risks & Mitigations

9.1 Risk 1: Cold-Start for Content Recommendations

Description: No historical labels for "best resource" for each query. Initial recommendations may be poor quality.

Impact:

- Low user satisfaction in first 2–4 weeks.
- Learners may abandon system if initial experience is bad.
- Data collection is slow (need real interactions to train bandit).

Mitigation:

1. **Heuristic baseline (M1):** Use metadata filters + semantic similarity to deliver "good enough" recommendations day-one.
2. **Weak labels (M1):** Bootstrap with Q&A logs and assessment data to create initial training set (5k–20k pairs).
3. **Teacher-in-the-loop (M1–M2):** Rapid labeling sprint (500–1k high-quality labels in 2 weeks).
4. **Active learning (M2+):** Prioritize uncertain cases for expert review, improve dataset quality iteratively.
5. **Bandit exploration (M4):** 20% exploration rate ensures system discovers good content even with poor initial policy.
6. **Fallback:** If retrieval confidence < 0.5 , offer to connect learner with human tutor.

Monitoring:

- Track: nDCG@5, user satisfaction (thumbs-up rate), session abandonment rate.
- Alert: If nDCG < 0.5 or satisfaction $< 60\%$ after Week 2, escalate to manual review.

9.2 Risk 2: Over-Long Resources (Minimality Failure)

Description: Retrieval returns hour-long videos or 50-page PDFs instead of short segments.

Impact:

- Poor user experience (cognitive overload).
- Learners skip resources, don't engage with content.
- Violates core product requirement (micro-learning).

Mitigation:

1. **Hard caps (M1):** Filter out any resource > 3 min (video) or > 2 pages (PDF).
2. **Sufficiency scoring (M2):** Rank by coverage-per-unit-time/pages, prefer shorter segments.

3. **Segmentation (M2):** Break videos/PDFs into chunks before retrieval (30–180s clips, paragraph-level segments).
4. **Bandit reward (M4):** Brevity bonus in reward function directly penalizes long resources.
5. **Post-retrieval summarization:** If segment still too long, provide extractive summary + link to full content.

Monitoring:

- Track: Median resource length, overkill rate (% over threshold), compression ratio.
- Alert: If median > 90s or overkill > 15%, audit retrieval pipeline for failures.

9.3 Risk 3: Hallucinations (Factual Errors)

Description: LLM generates incorrect questions, explanations, or hints not grounded in content.

Impact:

- Misleading learners (teach wrong information).
- Erosion of trust (educators flag system as unreliable).
- Potential harm (e.g., incorrect medical/legal information).

Mitigation:

1. **Retrieval-grounded generation:** All outputs cite source chunks (M1+).
2. **Answerability check (M3):** Before generating question, verify "Can this be answered from resource?"
3. **Factuality verification (M3):** NLI model checks entailment with source content, reject if contradiction.
4. **Confidence thresholding (M3):** If model confidence < 0.7, defer to human or flag for review.
5. **Refusal paths (M6):** If query is ambiguous or outside scope, politely refuse rather than hallucinate.
6. **Expert review loop (M3+):** Sample 50–100 outputs weekly, educators rate factuality, update prompts/adapters.

Monitoring:

- Track: Hallucination rate (via NLI + expert audit), refusal rate, learner flags ("this is wrong").
- Alert: If hallucination > 5%, pause deployment and investigate root cause.

9.4 Risk 4: Misaligned Difficulty (Questions Too Easy/Hard)

Description: Generated questions don't match learner's ability level (θ), leading to frustration or boredom.

Impact:

- Low engagement (learners skip questions).
- Poor learning outcomes (questions don't challenge appropriately).
- Inaccurate θ estimates (if all questions are too easy/hard).

Mitigation:

1. **IRT calibration (M4):** Estimate item difficulty (b) and discrimination (a) from pilot data.
2. **Adaptive questioning (M4+):** Select questions near learner's θ to maximize information.
3. **Anchor items (M4+):** Include pre-calibrated items in each test to link scales and detect drift.
4. **Recalibration cadence (M4+):** Re-estimate item parameters every 500 responses or quarterly.
5. **Drift detection (M4+):** Monitor $|b_{\text{current}} - b_{\text{initial}}| > 0.2$, flag for review.
6. **Weak difficulty estimates (M3):** Use expert judgment (1–10 scale) as initial b estimates before pilot.

Monitoring:

- Track: Item parameters (a , b , c), θ standard error (SE), test information curves.
- Alert: If $\text{SE} > 0.5$ (low precision) or item $a < 0.5$ (low discrimination), flag for recalibration.

9.5 Risk 5: Privacy & PII Leakage

Description: Learner PII (names, emails, performance data) leaked in logs, prompts, or outputs.

Impact:

- GDPR/FERPA violations (legal liability, fines).
- Loss of user trust, institutional adoption barriers.
- Reputational damage for Pearson.

Mitigation:

1. **Anonymization (M1):** Use hashed IDs (`learner_id = hash(email)`) in all logs and prompts.
2. **Data minimization (M1):** Don't log unnecessary PII (names, DOB, addresses).
3. **Role-based access (M6):** Only educators/admins see identifiable data, learners see only their own.
4. **PII redaction (M6):** Scan logs for names/emails/phone numbers, redact before storage.

5. **Encryption (M6):** Encrypt data at rest (database, logs) and in transit (TLS).
6. **Right to erasure (M6):** Implement GDPR compliance (delete learner data on request within 30 days).
7. **On-prem deployment option:** For institutions with strict privacy requirements, offer self-hosted version.

Monitoring:

- Track: PII detection alerts (automated scans), access logs (who viewed what data), data retention policies.
- Alert: If PII detected in logs or unauthorized access, escalate to security team immediately.

9.6 Risk 6: Model Drift & Degradation

Description: Foundation models update (GPT-4o \rightarrow GPT-4.5), prompts break, adapters become misaligned.

Impact:

- Sudden performance drop (questions become nonsensical, retrieval degrades).
- User complaints, loss of trust.
- Emergency rollback required.

Mitigation:

1. **Prompt versioning (M1+):** Store prompts in git repo, tag with model version, rollback if needed.
2. **Model pinning (M1+):** Use specific model versions (e.g., `gpt-4o-2024-08-01`) not `gpt-4o` (which auto-updates).
3. **Regression testing (M3+):** Before upgrading model, run evaluation harness on 200–500 test cases, compare to baseline.
4. **Adapter retraining (M5):** When new base model released, retrain LoRA adapters (takes 1–2 days).
5. **Gradual rollout (M6):** Canary deployment (10% traffic) for 1 week, full rollout only if metrics stable.
6. **Fallback (M6):** If new model underperforms, rollback to previous version within 1 hour.

Monitoring:

- Track: Model version in use, key metrics (nDCG, expert scores, $\Delta\theta$) per model version.
- Alert: If metrics drop $> 5\%$ after model upgrade, trigger rollback procedure.

9.7 Risk 7: Bias & Fairness

Description: System exhibits bias (demographic, topic, language) in recommendations or questions.

Impact:

- Unequal learning outcomes across demographic groups.
- Reinforcement of stereotypes (e.g., gender bias in examples).
- Legal/ethical concerns, institutional backlash.

Mitigation:

1. **Bias audit (M3, M6):** Sample 200–500 outputs, check for demographic bias (gender, race, age stereotypes).
2. **Diverse training data:** Ensure exemplars span diverse topics, perspectives, cultural contexts.
3. **Counterfactual testing:** Swap demographic attributes in prompts (e.g., "he" → "she"), check for output changes.
4. **Fairness metrics (M4+):** Compute $\Delta\theta$ by demographic group, flag if disparity > 0.1 (effect size).
5. **Content review:** Educators review questions/resources for stereotypes, update prompts/adapters if issues found.

Monitoring:

- Track: Bias metrics (demographic parity, equalized odds), content review flags.
- Alert: If bias detected (counterfactual test fails or disparity > 0.1), escalate to ethics review.

9.8 Risk Summary Table

Risk		Impact	Mitigation	Monitoring
Cold-start		High	Heuristics, weak labels, teacher-in-the-loop, exploration	nDCG, satisfaction, abandonment
Over-long resources		High	Hard caps, sufficiency scoring, segmentation, brevity reward	Median length, overkill rate
Hallucinations		High	Grounded generation, answerability checks, NLI verification	Hallucination rate, learner flags
Misaligned	diffi-	Medium	IRT calibration, adaptive questioning, drift detection	SE, item parameters, information
Privacy/PII		High	Anonymization, encryption, RBAC, right to erasure	PII detection, access logs
Model drift		Medium	Versioning, pinning, regression testing, gradual rollout	Metrics per model version
Bias & fairness		Medium	Bias audit, diverse data, counterfactual testing, fairness metrics	Demographic disparity, content flags

Table 6: Risk Summary

10 Deliverables per Milestone

10.1 Milestone 1: RAG Baseline

Code & Pipelines:

- Jupyter notebook: `01_rag_baseline.ipynb` (reproduces evaluation)
- Python modules: `retrieval.py`, `embedding.py`, `fusion.py`
- API: `POST /retrieve` endpoint with OpenAPI spec
- Docker image: Containerized RAG service for deployment

Data & Models:

- Data card: Content corpus stats (# videos/PDFs, total duration/pages, metadata schema)
- Embedding model: OpenAI `text-embedding-3-large` or self-hosted `bge-large-en-v1.5`
- BM25 index: Elasticsearch or custom index on corpus
- Vector DB: Pinecone or Weaviate collection with 100k–1M embeddings

Evaluation & Reports:

- Evaluation report: `nDCG@5`, `Recall@10`, median length, overkill rate (tables + charts)
- Test set: 200–300 queries with relevance labels (expert-annotated)
- Red-team cases: 50 adversarial/edge-case queries + failure analysis
- Decision memo: Go/no-go for M2 based on acceptance criteria

10.2 Milestone 2: Reranking & Segmentation

Code & Pipelines:

- Video processing: `video_segmenter.py` (ASR + scene detection + timestamp extraction)
- PDF processing: `pdf_sectionizer.py` (header detection + paragraph chunking)
- Cross-encoder reranker: `reranker.py` (HuggingFace model wrapper)
- API: `POST /retrieve_v2` with JSON schema for structured outputs

Data & Models:

- Model card: Cross-encoder (`ms-marco-MiniLM-L-12-v2`) specs, latency, performance
- ASR outputs: Whisper transcripts for video corpus (stored in DB)
- PDF segments: Section-level chunks with page ranges (stored in DB)

Evaluation & Reports:

- Evaluation report: `nDCG@5` (improved), compression ratio, segment examples
- Benchmark: Latency comparison (M1 vs. M2), cost per query
- Ablation study: BM25-only vs. Dense-only vs. Hybrid + reranking

10.3 Milestone 3: Pedagogy Tools v1

Code & Pipelines:

- Question generator: `question_gen.py` with few-shot prompts
- Rubric grader: `grader.py` with chain-of-thought prompts
- Hint generator: `hint_gen.py` with progressive scaffolding
- APIs: `POST /generate_question`, `POST /grade_response`, `POST /get_hint`

Data & Models:

- Prompt library: Few-shot exemplars for each Bloom level (10–20 per level)
- Rubric templates: 4-level rubrics (Novice/Developing/Proficient/Advanced) for common tasks
- Validation dataset: 200 generated questions with expert ratings

Evaluation & Reports:

- Evaluation report: Expert rubric scores (per dimension), Pass@1, hallucination rate
- Example outputs: 50 question/grade/hint triplets with expert annotations
- Failure analysis: Common error modes (ambiguous questions, off-topic, hallucinations)

10.4 Milestone 4: Bandit Optimization

Code & Pipelines:

- Bandit service: `bandit_policy.py` (Thompson Sampling or LinUCB)
- IRT module: `irt_estimator.py` (ability estimation, item calibration)
- Logging pipeline: Kafka producer + consumer, data warehouse schema
- A/B test framework: Randomization, metric computation, statistical tests

Data & Models:

- Logged data: 10k–50k interactions (context, action, reward, propensity)
- IRT parameters: (a, b, c) for each item, θ for each learner
- Bandit policy: Serialized model (Thompson Sampling parameters or LinUCB weights)

Evaluation & Reports:

- A/B test report: Control vs. treatment comparison on $\Delta\theta$, gain, minimality, satisfaction
- Telemetry dashboard: Real-time bandit diagnostics (exploration rate, reward trends, regret)
- Decision memo: Proceed to LoRA fine-tuning if $\Delta\theta$ improves by $\geq 10\%$

10.5 Milestone 5: LoRA Fine-Tuning

Code & Pipelines:

- Training scripts: `train_lora.py` for each adapter (question gen, grader, distractor, explainer)
- Inference pipeline: vLLM or Lorax adapter serving
- A/B test: Prompt-only vs. LoRA-adapted comparison

Data & Models:

- Training datasets: 500–2k exemplars per task (deduplicated, high-quality)
- LoRA adapters: 4 trained adapters (.safetensors files) + config files
- Model cards: Per adapter (architecture, training data, hyperparameters, performance)

Evaluation & Reports:

- A/B test report: Prompt-only vs. LoRA-adapted on expert scores, consistency, $\Delta\theta$
- Validation curves: Training/validation loss, perplexity over epochs
- Decision memo: Adopt LoRA if improvement $\geq 5\%$; otherwise revert to prompt-only
- Migration plan: Procedure for upgrading base model while preserving adapters

10.6 Milestone 6: Production Hardening

Code & Pipelines:

- Guardrails: `hallucination_detector.py`, `refusal_handler.py`, `pii_redactor.py`
- Monitoring: Grafana dashboards, Prometheus metrics, alert rules
- Compliance: GDPR/FERPA audit scripts, right-to-erasure handler
- Load testing: Locust or K6 scripts for 10k concurrent users

Data & Models:

- NLI model: DeBERTa-mnli for factuality checks
- Moderation API: OpenAI Moderation or Perspective API integration
- Telemetry schemas: Metrics definitions, alert thresholds

Evaluation & Reports:

- Compliance report: GDPR/FERPA checklist + accessibility audit (WCAG 2.1 AA)
- Load test report: P95/P99 latency, error rate, resource utilization under 10k users
- Runbooks: Incident response procedures for hallucination spikes, API outages, PII leaks
- Launch readiness review: Sign-off from security, legal, product teams

Dashboards & Documentation:

- Educator dashboard: Class-level and individual learner analytics
- Learner explanations: "Why this?" UI components with rationale
- User docs: Educator guide (100 pages) + learner guide (20 pages)
- Technical docs: API reference, architecture diagrams, deployment guide

10.7 Deliverable Checklist (All Milestones)

Category	Deliverables
Code & Pipelines	Notebooks, modules, APIs, Docker images, training scripts, inference pipelines
Data & Models	Datasets, embeddings, adapters, IRT parameters, prompt libraries, schemas
Evaluation & Reports	Metric tables, charts, A/B test results, failure analyses, decision memos
Documentation	Model cards, data cards, runbooks, user guides, API docs, architecture diagrams
Dashboards & Monitoring	Grafana/Prometheus, educator/learner dashboards, alert rules
Compliance & Security	GDPR/FERPA audits, PII redaction, encryption, incident response

Table 7: Deliverable Checklist

11 First 14 Days: Executable Task List

11.1 Objective

Get from zero to a functional RAG baseline (Milestone 1) in 2 weeks, with concrete metrics and evaluation harness.

11.2 Team Composition (Small Team)

- **1 ML Engineer:** Responsible for RAG pipeline, embeddings, retrieval.
- **1 Data Scientist:** Responsible for evaluation, metrics, analysis.
- **1 Content Engineer:** Responsible for content ingestion, ASR, parsing.
- **1 Product Manager (part-time):** Coordinate with educators, define test cases.

11.3 Day-by-Day Task Breakdown

11.3.1 Week 1 (Days 1–7): Content Ingestion & Baseline Retrieval

Day 1–2: Environment Setup & Content Audit

1. Set up cloud environment (AWS/GCP/Azure), provision GPUs (optional for local embedding).
2. Set up vector DB (Pinecone free tier or Weaviate Docker) and Elasticsearch.
3. Audit content corpus: Count videos, PDFs, total duration/pages, identify metadata fields (title, topic, keywords).
4. **Output:** Environment ready, content inventory spreadsheet.

Day 3–4: ASR & PDF Parsing

1. Videos: Run Whisper ASR on 100–500 sample videos (batch job, 1–2 hours per 10 hours of video).
2. PDFs: Parse with PyMuPDF, extract text, identify section headers, chunk by paragraphs.
3. Store: ASR transcripts and PDF text in database (Postgres or MongoDB).
4. **Output:** 100–500 videos transcribed, 500–1k PDFs parsed.

Day 5–6: Embedding & Indexing

1. Chunk content: 30–180s for videos (sentence boundaries), paragraphs for PDFs (100–500 tokens).
2. Embed chunks: OpenAI `text-embedding-3-large` (or self-hosted `bge-large-en-v1.5`).
3. Index: Upload embeddings to vector DB, build BM25 index on chunk text.
4. Metadata: Store title, topic, duration/length, `chunk_id`, `parent_resource_id`.
5. **Output:** 10k–100k chunks indexed in vector DB + BM25.

Day 7: Hybrid Retrieval Implementation

1. Implement: BM25 retrieval (top-50), dense retrieval (top-50), RRF fusion ($0.3 \text{ BM25} + 0.7 \text{ dense}$).
2. Test: 10 sample queries, inspect top-10 results manually.
3. Filter: Apply hard caps (videos ≤ 3 min, PDFs ≤ 2 pages).
4. **Output:** Functional `/retrieve` API endpoint.

11.3.2 Week 2 (Days 8–14): Evaluation & Baseline Metrics**Day 8–9: Test Set Creation**

1. Collect 200–300 test queries: Sample from historical Q&A logs, generate synthetic queries (LLM), recruit educators to write queries.
2. Stratify: Simple (factual) vs. complex (conceptual), short (1 word) vs. long (full sentence).
3. **Output:** Test set CSV: (query_id, query_text, topic, complexity).

Day 10–11: Expert Labeling

1. Run retrieval on 200–300 test queries, get top-10 results per query.
2. Recruit 2–3 educators, each labels 100 queries (overlap 20% for inter-rater agreement).
3. Labeling UI: Simple web form with query, top-10 results, relevance rating (0–3: not/some-what/relevant/highly relevant).
4. **Output:** Labeled dataset: (query_id, resource_id, relevance_score).

Day 12: Evaluation Harness

1. Implement metrics: nDCG@5, nDCG@10, Recall@10, median length, overkill rate.
2. Jupyter notebook: Load test set, run retrieval, compute metrics, generate report (tables + plots).
3. **Output:** `01_eval_baseline.ipynb` with metric results.

Day 13: Red-Team Testing

1. Adversarial queries: Ambiguous ("What is X?"), out-of-scope ("How to hack?"), edge cases (typos, jargon).
2. Test refusal logic: "I don't have information on that" for out-of-scope.
3. Document: Failure modes (retrieval returns irrelevant, over-long, or no results).
4. **Output:** Red-team report with 50 test cases + failure analysis.

Day 14: Report & Decision Memo

1. Compile: Evaluation report (metrics table, example retrievals, failure analysis).
2. Decision memo: Go/no-go for M2 based on acceptance criteria (nDCG@5 > 0.6 , Recall@10 > 0.70).
3. Presentation: 15-minute review with stakeholders (product, engineering, educators).
4. **Output:** PDF report + slides for review meeting.

11.4 Task Assignment Table

Day	Task	Owner	Deliverable
1–2	Environment setup, content audit	ML Engineer	Inventory spreadsheet
3–4	ASR & PDF parsing	Content Engineer	Transcripts & parsed PDFs
5–6	Embedding & indexing	ML Engineer	Vector DB + BM25 index
7	Hybrid retrieval implementation	ML Engineer	<code>/retrieve</code> API
8–9	Test set creation	Data Scientist + PM	Test set CSV
10–11	Expert labeling	PM + Educators	Labeled dataset
12	Evaluation harness	Data Scientist	Eval notebook
13	Red-team testing	All team	Red-team report
14	Report & decision memo	Data Scientist + PM	PDF report + slides

Table 8: Task Assignment (Days 1–14)

11.5 Daily Standup Agenda

1. Yesterday: What did I complete?
2. Today: What am I working on?
3. Blockers: Any dependencies or issues?
4. Metrics: Current progress toward Day 14 acceptance criteria.

11.6 Success Criteria (End of Day 14)

- **Functional API:** `POST /retrieve` returns top-3 resources in $< 8s$ (P95).
- **Metrics:** $nDCG@5 > 0.6$, $Recall@10 > 0.70$, median length $< 90s$ (videos) / < 1.5 pages (PDFs).
- **Evaluation harness:** Reproducible notebook with automated metric computation.
- **Red-team:** 50 adversarial cases documented with failure modes.
- **Decision:** Go/no-go for M2 based on acceptance criteria.

11.7 Tools & Resources (Quick Start)

- **ASR:** OpenAI Whisper API or `faster-whisper` (self-hosted)
- **PDF parsing:** PyMuPDF (`fitz`) or Apache PDFBox
- **Embeddings:** OpenAI `text-embedding-3-large` or HuggingFace `sentence-transformers`
- **Vector DB:** Pinecone (free tier) or Weaviate (Docker)
- **BM25:** Elasticsearch (Docker) or `rank_bm25` (Python library)

- **Notebooks:** Jupyter or Google Colab
- **API:** FastAPI or Flask
- **Labeling:** Label Studio or Google Forms

Estimated Cost (Days 1–14):

- OpenAI embeddings: \$50–\$100 (100k chunks)
- Whisper ASR: \$50–\$200 (100–500 videos)
- Vector DB: Free (Pinecone tier) or \$50/month (Weaviate cloud)
- Compute: \$100–\$200 (cloud GPUs/CPU for 2 weeks)
- **Total:** \$250–\$650 for first 14 days