

Contents

RADIANT Expert System Adapters	1
Tenant-Trainable Domain Intelligence	1
Executive Summary	2
1. The Problem with Generic AI	2
1.1 One-Size-Fits-None	2
1.2 The Training Gap	2
2. Expert System Adapters: The Solution	2
2.1 Tri-Layer Architecture	2
2.2 Automatic Learning Pipeline	3
2.3 Feedback Signals	3
3. Domain Expertise System	4
3.1 Domain Detection	4
3.2 Domain-Specific Adapters	4
3.3 Auto-Selection Algorithm	4
4. Training Pipeline	5
4.1 Candidate Collection	5
4.2 Training Schedule	5
4.3 Contrastive Learning	5
5. Safety & Rollback	6
5.1 Automatic Rollback	6
5.2 A/B Testing	6
5.3 Version Control	6
6. Implementation Files	6
6.1 Database Schema	6
6.2 Services	7
6.3 Admin API	7
6.4 Admin UI	7
7. Competitive Advantages	7
7.1 vs. Generic AI Platforms	7
7.2 vs. Custom Fine-Tuning	7
8. 2029 Vision	8
8.1 Short-term (2026)	8
8.2 Medium-term (2027)	8
8.3 Long-term (2029)	8
9. Getting Started	8
9.1 Enable Expert System Adapters	8
9.2 Monitor Learning Progress	8
9.3 Domain Configuration	9

RADIANT Expert System Adapters

Tenant-Trainable Domain Intelligence

Version: 1.0 | January 2026

Cross-AI Collaborative Design: Claude Opus 4.5 + Gemini

Executive Summary

Expert System Adapters (ESA) represent RADIANT's approach to tenant-trainable domain intelligence. Unlike generic AI models that treat all queries equally, ESA enables each tenant to build specialized AI expertise that continuously improves through interaction feedback.

Key Innovation: Every tenant develops their own “expert” that learns their specific domain language, preferences, and quality standards—without requiring any ML expertise from administrators.

1. The Problem with Generic AI

1.1 One-Size-Fits-None

Traditional AI platforms offer the same model to all customers:

- A law firm gets the same AI as a marketing agency
- Medical terminology isn't prioritized for healthcare providers
- Industry-specific jargon goes unrecognized
- Quality standards vary by domain but models can't adapt

1.2 The Training Gap

Organizations want AI that understands them, but:

- Fine-tuning requires ML expertise (costly, rare)
- Training data curation is time-consuming
- Model updates risk regression
- No visibility into what the AI has “learned”

2. Expert System Adapters: The Solution

2.1 Tri-Layer Architecture

ESA implements a three-layer adapter stack that composes personalization at multiple levels:

Final Model Weights
$$W_{Final} = W_{Genesis} + W_{Cato} + W_{User}$$

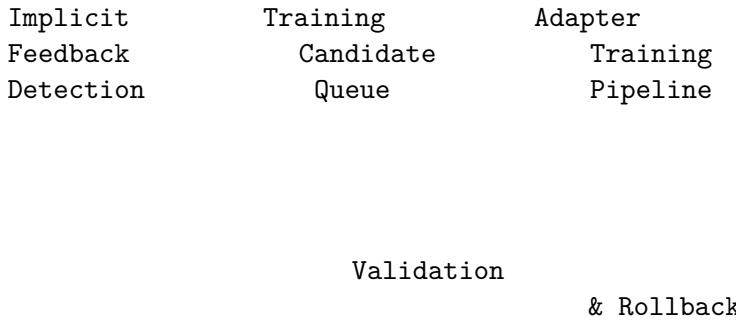
Layer 0	Layer 1	Layer 2
Genesis	Cato	User
(Base)	(Global)	(Personal)
Frozen	Pinned	LRU Eviction

Layer	Name	Purpose	Management
0	Genesis	Base model weights	Frozen, never modified
1	Cato	Global constitution, safety, tenant values	Pinned in memory, never evicted
2	User	Personal preferences, interaction style	LRU eviction when memory constrained
3	Domain	Specialized expertise (optional)	Auto-selected by domain detection

2.2 Automatic Learning Pipeline

ESA learns from every interaction without manual intervention:

User Interaction



2.3 Feedback Signals

ESA captures both explicit and implicit quality signals:

Signal Type	Weight	Interpretation
Copy Response	+0.80	High utility - user copied the output
Thumbs Up	+1.00	Explicit positive feedback
Follow-up Question	+0.30	Partial success, needs more
Long Dwell Time	+0.40	User engaged with response
Regenerate Request	-0.50	Response wasn't satisfactory
Abandon Conversation	-0.70	Complete failure
Rephrase Question	-0.50	Original response missed the mark
Thumbs Down	-1.00	Explicit negative feedback

3. Domain Expertise System

3.1 Domain Detection

RAWS (RADIANT Adaptive Weighted Selection) automatically detects query domains:

Domain	Subspecialties	Example Triggers
Legal	Contract, IP, Employment, Litigation	“pursuant to”, “liability”, “indemnify”
Medical	Clinical, Research, Administrative	“diagnosis”, “contraindication”, “ICD-10”
Financial	Accounting, Investment, Compliance	“GAAP”, “depreciation”, “quarterly”
Engineering	Software, Mechanical, Electrical	“API”, “architecture”, “implementation”
Creative	Marketing, Design, Content	“brand voice”, “engagement”, “campaign”
Research	Academic, Scientific, Analysis	“hypothesis”, “methodology”, “peer-reviewed”
Operations	HR, Project Management, Logistics	“workflow”, “onboarding”, “KPI”

3.2 Domain-Specific Adapters

Each domain can have specialized LoRA adapters:

```
interface DomainLoraAdapter {
    id: string;
    tenantId: string;
    domain: string;
    subdomain?: string;
    adapterName: string;
    baseModel: string;
    adapterVersion: number;
    s3Bucket: string;
    s3Key: string;
    trainingCandidatesCount: number;
    lastTrainedAt?: Date;
    accuracyScore?: number;
    domainRelevanceScore?: number;
    userSatisfactionScore?: number;
    status: 'training' | 'validating' | 'active' | 'deprecated' | 'failed';
}
```

3.3 Auto-Selection Algorithm

When a query arrives, ESA selects the optimal adapter:

```
Score = (0.3 × DomainMatch)
      + (0.1 × SubdomainBonus)
```

```
+ (0.25 × SatisfactionScore)
+ (0.1 × VolumeScore)
+ (0.05 × ErrorRate)
+ (0.2 × RecencyScore)
```

Selection threshold: Score > 0.5 to use adapter (else fallback to base model)

4. Training Pipeline

4.1 Candidate Collection

Training candidates accumulate based on configurable thresholds:

Setting	Default	Description
<code>min_candidates_for_training</code>	25	Minimum total candidates before training
<code>min_positive_candidates</code>	15	Minimum positive examples required
<code>min_negative_candidates</code>	5	Minimum negative examples for contrastive learning

4.2 Training Schedule

Configurable training frequency with intelligent scheduling:

Frequency	Best For	Auto-Optimal Time
Daily	High-volume tenants	Detects lowest-usage hours
Twice Weekly	Medium activity	Balances freshness/cost
Weekly	Standard deployments	Default for most tenants
Biweekly	Low activity	Conservative approach
Monthly	Minimal changes	Stability-focused

4.3 Contrastive Learning

ESA uses both positive and negative examples for better learning:

Positive Examples: High-rated responses, copied text, explicit thumbs-up **Negative Examples:** Regenerated responses, abandoned conversations, explicit thumbs-down

```
-- Negative learning candidate categories
'factual_error'          -- Incorrect information
'incomplete_answer'       -- Missing key details
'wrong_tone'               -- Inappropriate style
'too_verbose'              -- Unnecessarily long
'too_brief'                -- Lacking detail
'off_topic'                 -- Didn't address question
'harmful_content'           -- Safety violation
'formatting_issue'          -- Poor structure
```

```
'code_error'           -- Broken code
'unclear_explanation' -- Confusing response
```

5. Safety & Rollback

5.1 Automatic Rollback

ESA monitors adapter performance and automatically rolls back if quality degrades:

```
// Rollback triggers
const rollbackConditions = {
  satisfactionDrop: 10,      // % drop from baseline
  errorRateIncrease: 5,     // % increase in errors
  latencyIncrease: 50,      // % increase in response time
  minSampleSize: 100,        // Minimum requests before evaluation
};
```

5.2 A/B Testing

New adapters are deployed with gradual rollout: 1. **Shadow Mode** (0% traffic): Adapter runs but results not returned 2. **Canary** (5% traffic): Small percentage gets new adapter 3. **Gradual Rollout** (5% → 25% → 50% → 100%): Progressive increase 4. **Full Deployment**: All traffic uses new adapter

5.3 Version Control

Every adapter version is preserved: - Rollback to any previous version - Compare performance across versions - Audit trail of all training runs

6. Implementation Files

6.1 Database Schema

Table	Purpose
enhanced_learning_config	Per-tenant configuration
implicit_feedback_signals	Captured feedback signals
negative_learning_candidates	Contrastive learning examples
active_learning_requests	User feedback requests
domain_lora_adapters	Domain-specific adapters
domain_adapter_training_queue	Training job queue
adapter_usage_logs	Adapter invocation tracking
pattern_cache	Successful response patterns

Migration: packages/infrastructure/migrations/108_enhanced_learning.sql

6.2 Services

Service	Purpose
<code>enhanced-learning.service.ts</code>	Core learning orchestration
<code>lora-inference.service.ts</code>	Tri-layer adapter inference
<code>adapter-management.service.ts</code>	Adapter selection and management

6.3 Admin API

Base: /api/admin/learning

Endpoint	Method	Purpose
/config	GET/PUT	Configuration management
/domain-adapters	GET	List domain adapters
/domain-adapters/{domain}	GET	Get active adapter for domain
/training/queue	GET	View training queue
/training/trigger	POST	Manually trigger training
/performance/{adapterId}	GET	Adapter performance metrics

6.4 Admin UI

Location: /models/lora-adapters

Features: - Tri-layer architecture visualization - Adapter registry by layer (Global/User/Domain) - Configuration management - Warmup controls - Performance metrics

7. Competitive Advantages

7.1 vs. Generic AI Platforms

Capability	RADIANT ESA	Generic Platforms
Per-tenant customization	Automatic	Same model for all
Domain expertise	Learned	Generic
Implicit feedback	11 signal types	Manual ratings only
Contrastive learning	Positive + negative	Positive only
Automatic rollback	Built-in	Manual monitoring
Zero ML expertise required	Fully automatic	Requires ML team

7.2 vs. Custom Fine-Tuning

Aspect	RADIANT ESA	Custom Fine-Tuning
Time to value	Hours	Weeks-months
ML expertise needed	None	Senior ML engineer

Aspect	RADIANT ESA	Custom Fine-Tuning
Data curation	Automatic	Manual
Continuous learning	Always on	Batch retraining
Regression protection	Automatic rollback	Manual testing
Cost	Included	\$50K-500K/year

8. 2029 Vision

8.1 Short-term (2026)

- Tri-layer adapter architecture
- Implicit feedback detection
- Contrastive learning
- Automatic rollback
- Domain auto-selection

8.2 Medium-term (2027)

- Cross-tenant knowledge sharing (with privacy guarantees)
- Real-time adapter updates (no batch training)
- Multi-modal expertise (text, code, images)
- Expert marketplace for adapter sharing

8.3 Long-term (2029)

- Fully autonomous expertise development
- Zero-shot domain adaptation
- Cross-lingual expertise transfer
- Self-improving training pipelines

9. Getting Started

9.1 Enable Expert System Adapters

1. Navigate to **Admin Dashboard** → **Models** → **LoRA Adapters**
2. Enable “LoRA Adapters” toggle
3. Configure adapter stacking options:
 - Use Global Adapter (Cato): Recommended ON
 - Use User Adapter: Recommended ON
 - Auto Selection: Recommended ON
4. Save configuration

9.2 Monitor Learning Progress

1. Check **Training Queue** for pending candidates
2. Review **Adapter Registry** for active adapters

3. Monitor **Performance Metrics** for quality trends
4. Use **Warmup** to pre-load frequently-used adapters

9.3 Domain Configuration

1. Navigate to **Learning → Domain Adapters**
 2. View auto-detected domains with training candidates
 3. Optionally trigger manual training for priority domains
 4. Review adapter performance by domain
-

Expert System Adapters: Where every tenant becomes an AI domain expert.