

AELP Complete System Architecture Overview

Version 2.0

September 29, 2025

Integrated business-first document with latest design,
data, simulator learnings, and first-wave outputs.

Aura Engineering Team

Confidential and Proprietary

Contents

- 1 Executive Summary 2**
 - 1.1 The Challenge 2
 - 1.2 Our Solution 2
 - 1.3 This Week’s Plan 2
- 2 Problem Framing & Goals 3**
 - 2.1 Why Simulate Real Life for Reinforcement Learning 3
 - 2.2 Key Questions Answered 3
 - 2.3 Constraints and Success Metrics 3
- 3 Plain-Language Glossary & Assumptions 4**
- 4 System Architecture 5**
- 5 Connectors & Data Inventory 6**
 - 5.1 Connectors Status 6
 - 5.2 BigQuery Datasets 6
- 6 Feature & Ranking Layer 7**
- 7 Forecasting (Placement-Aware) 8**
- 8 Offline RL Simulator 9**
- 9 First-Wave Outputs 10**
- 10 Workflow & Roadmap 11**
- 11 Status & Risks 12**
- 12 Appendix: Data Lineage 13**

Chapter 1

Executive Summary

1.1 The Challenge

The Aura Experiential Learning Platform (AELP) optimizes behavioral health marketing spend across digital channels. Traditional approaches yield unpredictable customer acquisition costs (CAC) ranging from \$150 to \$400.

1.2 Our Solution

AELP simulates auctions and user journeys, forecasts CAC/volume with uncertainty, and uses Thompson sampling to allocate budget across creatives.

1.3 This Week's Plan

- Launch Security slate (8 creatives) at \$30k/day with p50 CAC of \$166–\$289.
- Launch Balance slate (8 creatives) at \$30k/day with p50 CAC of \$82–\$142.
- Monitor daily performance within p10–p90 bounds; adjust if outside.

Key Performance Metrics

Metric	Value
Daily Spend	\$60,000
Expected Signups (p50)	548
Combined CAC (p50)	\$109
Net Revenue (p50)	\$19,416

Confidence: precision@10 = 30%, calibration reliability = 0.85+.

Chapter 2

Problem Framing & Goals

2.1 Why Simulate Real Life for Reinforcement Learning

Traditional A/B testing is slow and expensive. Offline simulation explores strategies safely by modeling auctions, user journeys, temporal dynamics, and uncertainty.

2.2 Key Questions Answered

1. Which creatives to run? Top-8 ranked by expected value and uncertainty.
2. Where to place them? Optimal mix across feed/stories/reels by baselines.
3. How much to spend? Thompson sampling with per-creative caps.
4. Expected CAC & volume? Probabilistic p10/p50/p90 forecasts.

2.3 Constraints and Success Metrics

Hard Constraints

- CAC targets: Security $\leq \$240$; Balance $\leq \$200$. Budget caps : $\$30k/day$ per product; $min 100 signups/day$.

Chapter 3

Plain-Language Glossary & Assumptions

p10/p50/p90 — Uncertainty percentiles; p50 = median.

Conformal bound — Lower-bound guarantee on predictions.

Placement — Feed, Stories, Reels, Audience Network.

Thompson Sampling — Balances exploration vs exploitation.

AOV — Revenue per subscription: Security \$200; Balance \$120.

Chapter 4

System Architecture

Raw data from platform APIs and vendors flows to BigQuery; feature engineering builds creative signals; ranking predicts CTR/CVR with calibration; forecasting projects CAC/volume by placement; the RL planner allocates budgets; the Creative Planner packages a launch slate.

Chapter 5

Connectors & Data Inventory

5.1 Connectors Status

BigQuery (green), Meta Ads API (green), SearchAPI vendor (yellow), Google Analytics (yellow), Google Ads (yellow), Impact.com (red), Redis cache (green).

5.2 BigQuery Datasets

Meta ad performance (by placement), creative objects, forecasts, RL simulations, and planner reports under the training project; 30-day backfill completed for major placements on 2025-09-28.

Chapter 6

Feature & Ranking Layer

Text, vision, and historical features feed calibrated models. Accuracy snapshot: Precision@5=26.7%, Precision@10=30.0%, AUC-ROC=0.73, Calibration=0.85+.

Chapter 7

Forecasting (Placement-Aware)

Baselines per placement (CPM/CTR/CVR) drive Monte Carlo projections. Security slate p50 CAC range \$166–\$289; Balance slate p50 \$82–\$142.

Chapter 8

Offline RL Simulator

Thompson sampling with safety caps converges in 3–5 days; outputs per-creative budgets with early-stop rules.

Chapter 9

First-Wave Outputs

30-day combined outlook (daily): Spend \$60k, Signups p50 548, CAC p50 \$109, Revenue p50 \$79,416, Net p50 \$19,416.

Auction vs Thompson (New Result)

Slate Comparison at \$30k/day (p50)

Slate	Avg CAC	Sum Signups	P@10 (proxy)
Thompson (TS)	\$255.06	965.3	0.375
Auction-aware (AU)	\$228.55	1091.3	0.500
RecSim (RS)	\$202.22	1231.8	1.000

Notes: AU uses AuctionGym with CPM calibration; RS is persona-based and optimistic (higher CAC MAPE). TS uses baseline forecasts; AU shows lower CAC/higher volume.

Stability: AU top-5 stable under bid $\pm 20\%$ and quality $\pm 10\%$.

Significance (bootstrap, ref=CAC p50): TS vs AU $\Delta\text{CAC}=\$26.41$ $[-11.76, 64.31]$ — trending better; TS vs RS $\Delta\text{CAC}=\$52.70$ $[14.04, 85.79]$.

Chapter 10

Workflow & Roadmap

Daily ops timeline (refresh, review, adjust, test). 90-day roadmap includes 90-day backfill, video scoring v1, real-time bidding pilot, cross-channel attribution, expansion to Calm track.

Chapter 11

Status & Risks

Working well: placement-aware forecasting, planner, offline sim, US baselines. In progress: full backfill, EU/UK coverage, rate-limit hardening. Gaps: Ad Library coverage, vendor API reliability, video scoring, ATT constraints. Risks: model drift, rate limits, compliance, overspend, tracking failures.

Chapter 12

Appendix: Data Lineage

End-to-end lineage from sources (Meta/SearchAPI/GA4) through baselines, scoring, forecasts, RL simulation, and Planner outputs.