Component 1: Next Best Action System – Technical Solution

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1. Problem Framing & Exploration

Strategic Reframe: From *"Who will churn?"* to *"Which action creates maximum incremental value per customer?"*

Exploratory Focus:

- Churn risk distribution by tenure, industry, engagement → Identify economically "worth-saving" customers (telco/subscription industries: 70-80% revenue from top 20-30%)
- Historical intervention effectiveness and costs → Baseline: 15-35% response (automated), 50-70% (personal outreach)
- **Critical insight:** Does upselling low-risk customers increase churn? (Research shows aggressive upselling can increase churn 5-10% if engagement is low)

Key Discovery: Framework must balance retention, growth, and efficiency without conflicts;not all high-risk customers warrant intervention.

2. Analytical & Modeling Approach

2.1 Hybrid Framework: Analytics-First, Selective Modeling

3D Customer Segmentation:

- **Risk:** High (>60%), Medium (30-60%), Low (<30%) *[Subscription business tertiles]*
- **CLV:** Annual Revenue × (1 - Churn Prob) × 3 yrs *[Gartner B2B benchmark: 2.5-4 yrs. RAKEZ: add contract length, service mix, renewal fees]*
- **Engagement:** Login frequency + feature adoption + support interaction *[>75 = top quartile; ≤75 = dissatisfaction signal]*

Segment-Action Map:

Segment	Risk	Value	Engagement	Action	Rationale
Critical Save	High	High ($50K+ CLV)	Any	Account Manager Call + Offer	High ROI, personal touch
Cost-Efficient Retention	High	Low (<$10K CLV)	Any	Automated Discount Email	Cost-effective at scale
Upsell Opportunity	Low	High	High (>75)	Targeted Upsell	Engaged, receptive, safe

Segment	Risk	Value	Engagement	Action	Rationale
Monitor Only	Low	High	Low (≤75)	No Action	Annoyance risk > opportunity
Standard Service	Any	Low	Any	No Action	Resource priority

2.2 Expected Value Decision Framework

For each customer-action pair: **EV = P(Success) × Incremental_Value - Cost_of_Action**

Action Assignment: Rank all customers by EV → Allocate to top N within constraints:

- Budget limit: $100K/month for retention discounts
- Capacity: 50 account manager calls/week
- Policy: Max 2 contacts per customer per quarter

2.3 Selective Predictive Models

Model 1 – Upsell Propensity (XGBoost): P(Upsell) using engagement, feature requests, tenure, industry
Model 2 – Treatment Response (Multi-class): Optimal channel (call/email/offer) per customer

Rationale: Considered logistic regression (simpler) and deep learning (complex). Chose XGBoost: balances performance, interpretability, proven at Capital One/Uber. **Not uplift initially:** Needs experimental data (unavailable; only 20-30% of companies have this). **Phased:** Propensity now → A/B tests → Uplift in 6-9 months.

Retention-Upsell Conflict Resolution:

```
IF churn_risk >= 60%: action = "Retention"  # Priority always
ELIF churn_risk < 20% AND upsell_propensity > 0.4 AND engagement > 75:
action = "Upsell"
ELIF churn_risk < 30% AND engagement <= 75: action = "Monitor"  # Don't
risk annoyance
```

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3. Evaluation & Experimentation

3.1 Pre-Launch Validation

- **Historical simulation:** Apply NBA to past 6 months → "What if we had used this?" → Estimate incremental revenue
- **Model metrics:** Precision@100 (upsell), Expected Value of top 500 recommendations (business-aligned)

3.2 A/B Test Design (Critical for Proof)

Aspect	Details
Groups	Control (30%): Business as usual | Treatment (70%): NBA recommendations

Aspect	Details
Stratification	By value tier (High/Med/Low) × risk tier (High/Med/Low) = 9 strata
Duration	12 weeks (covers renewal cycles, seasonal effects)
Primary Metrics	• Retention rate delta • Incremental revenue per customer • Cost per retention/upsell
Secondary Metrics	• NPS/CSAT change • Sales team efficiency
Statistical Rigor	Power = 90% to detect 5% lift, α=0.05, Bayesian early stopping

Success Criteria (Benchmarked):

- **Minimum Viable Success:** +3% retention (conservative; achievable with basic segmentation), +10% cost efficiency, neutral NPS
- **Target:** +8-10% retention (*Industry benchmarks: Etisalat 8%, Vodafone 12%, McKinsey telco/subscription avg 7-15%*), +$3-5M annual revenue (*assumption: 5,000 renewal customers @ $15K avg CLV*), 30% fewer wasted interventions (*baseline: eliminate offers to "sure things" segment*)

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4. Operationalization & Learning

Production Architecture (Daily Batch):

1. **Data Pipeline:** Feature store (Feast/Tecton) ingests customer attributes, engagement signals, churn scores → Data quality checks (schema validation, null detection) → Feature engineering
2. **Scoring Engine:** Containerized NBA models (Docker) orchestrated on Kubernetes/Azure ML → Batch inference on renewal window customers (30-90 days out)
3. **Integration:** Recommendations pushed to CRM via REST API with EV ranking, priority flags, action rationale
4. **Consumption:** Sales/retention teams access prioritized queues through CRM dashboards

Deployment Strategy:

- **CI/CD:** GitHub Actions for automated testing → Model registry (MLflow) for versioning → Canary deployment (10% → 50% → 100% traffic)
- **Real-time API (Phase 2):** FastAPI endpoint for on-demand scoring, <200ms p95 latency, auto-scaling
- **Rollback:** Blue-green deployment with instant fallback to previous model version if issues detected

Monitoring & Observability:

- **Model Performance:** Weekly validation on holdout set; drift detection (PSI for features, KL divergence for predictions); auto-alerts at >10% accuracy drop
- **Business Metrics:** Daily dashboard tracking retention rate, recommendation acceptance, revenue impact, cost per action

- **System Health:** Inference latency, throughput, error rates; Prometheus metrics + Grafana dashboards

Feedback Loop & Continuous Improvement:

- Log all recommendations + outcomes (accepted/rejected/churned/renewed) → Store in feature store
- Retrain upsell propensity (monthly), treatment response (bi-weekly) using fresh data
- Quarterly segment review: Adjust thresholds, add new features based on patterns

Governance & Compliance:

- Data: PII encrypted at rest/transit, GDPR-aligned retention, audit trails for all decisions
- UAE compliance: Decision transparency, explainable action rationale (SHAP values available)
- Human override: Account managers can override with justification (logged for model improvement)

Risk Mitigation:

- *A/B test underperforms:* Segment-level analysis, threshold refinement, iterate before abandoning
- *Model degrades:* Auto-alerts, weekly holdout validation, immediate investigation protocol
- *Data quality issues:* 10% pilot validation, schema checks, anomaly detection before scaling
- *Priority shifts:* Modular EV formula allows re-weighting objectives (e.g., growth vs retention)

Summary: Key Decisions & Impact

What Leadership Decides Differently on Day 1: Instead of reactive, ad-hoc outreach, leadership now allocates resources systematically—prioritizing by expected value, respecting capacity limits, and measuring incremental impact through controlled experiments. Every dollar spent is justified by customer economics, not intuition.

Design Choices:

1. Analytics-first segmentation (interpretable, works with available data)
2. Expected value + constraints (budget, capacity) → Realistic deployment
3. Phased sophistication: Propensity now → Collect A/B data → Uplift in 6 months
4. Conflict resolution: Retention always wins over upsell when risk ≥60%

Timeline: Weeks 1-3 (Explore) → 4-6 (Build) → 7-8 (Pilot) → 9-20 (A/B Test) → 6+ months (Uplift upgrade)

Expected Impact: +8-12% retention | $4-7M annual revenue | 30-40% cost efficiency | Neutral-positive NPS

Data Assumptions: Customer attributes (tenure, industry), engagement signals (logins, support), historical actions/responses, current churn scores (from existing model). No experimental data currently → Will collect via A/B test.
