Audience Validation Framework

Overview

This document describes the audience validation approach used to measure and compare the quality of audiences built on the Akkio + Affinity Solutions (AFS) data platform. The framework provides a standardized, repeatable methodology for evaluating how well any audience — whether a known-shopper seed, a lookalike expansion, or a propensity-scored cohort — predicts real consumer purchase behavior during a future holdout period.

The goal is to provide **apples-to-apples comparisons** across audience construction methods, enabling data-driven decisions about which approach delivers the highest-quality audiences for activation.

Key Concepts

What We Measure

Every audience is evaluated against the same set of metrics, calculated over a **holdout window** — a time period that was deliberately excluded when the audience was built. This ensures we are measuring true predictive power, not just historical behavior.

Metric	Formula	What It Tells You
Total Audience IDs	Count of distinct IDs in the audience	Audience reach / size
Active Matched IDs	Audience IDs with any transaction in the holdout period	Observable panel coverage within the audience
Brand Shoppers	Audience IDs with at least one brand transaction in holdout	How many audience members actually purchased
Brand Transactions	Total brand transactions from audience members in holdout	Volume of purchase activity

Metric	Formula	What It Tells You
Brand Spend	Total dollar amount of brand transactions in holdout	Revenue impact
Shop Rate	Brand Shoppers / Active Matched IDs	% of active audience members who purchased the brand
Spend Rate	Brand Spend / Active Matched IDs	Average brand spend per active audience member
Avg Ticket	Brand Spend / Brand Transactions	Average purchase size
Avg Transactions per Shopper	Brand Transactions / Brand Shoppers	Purchase frequency among converters

> **Why Active Matched IDs is the denominator (not Total Audience IDs):**
> Not every individual in the panel will have observable transaction activity in any given month. Using Total Active Matched IDs — audience members who had at least one transaction of *any* kind during the holdout — ensures we measure audience quality against observable behavior, rather than penalizing for panel coverage gaps.

Seed vs. Lookalike — Why Both Matter

Audience Type	What It Measures	Expected Behavior
Seed (Known Shoppers)	Retention / repeat purchase — "Do existing buyers keep buying?"	Higher shop rate (selecting on known buyers)
Lookalike / Propensity	Acquisition / prediction — "Can we find NEW brand shoppers before they buy?"	Lower shop rate, but demonstrates true predictive lift

A **seed audience** of known brand shoppers validated in a holdout window measures **retention** — these individuals already purchased, so the shop rate will be naturally high. This is useful for understanding audience stickiness but does not demonstrate predictive modeling power.

A **lookalike audience** or **propensity-scored cohort** of individuals who have *not* been observed purchasing the brand measures **acquisition** — the ability to identify future brand shoppers before they convert. This is the more meaningful test of audience quality and the direct comparison between modeling approaches.

Validation Methodology

Timeline Split

The validation uses a strict temporal holdout design to prevent data leakage:

Period	Role
All data through the build cutoff date	Used for audience construction (seed identification, feature engineering, model training)
Holdout window (post-cutoff)	Used **exclusively** for measuring audience performance — never seen during audience building

For the current validation cycle, the holdout window is **September 1, 2025 through September 30, 2025**.

How Validation Works

```
┌─────────────────────────────────────┐     ┌──────────────────────────┐
│          AUDIENCE BUILDING          │     │    HOLDOUT VALIDATION    │
│                                     │     │                          │
│  Transaction history + attributes   │     │  Unseen future period    │
│  used to identify seeds and build   │────▶│  used to measure actual  │
│  lookalike/propensity audiences     │     │  purchase behavior       │
│                                     │     │                          │
│  ◀── All data through cutoff ──▶    │     │  ◀── Holdout window ──▶  │
└─────────────────────────────────────┘     └──────────────────────────┘
```

Step-by-step process:

1. **Build the audience** using all transaction and attribute data up to the cutoff date
2. **Freeze the audience** — the list of IDs is fixed before looking at holdout data
3. **Join audience IDs** against all transactions in the holdout window
4. **Identify active members** — audience IDs that had *any* transaction (any brand) during the holdout
5. **Identify brand converters** — audience IDs that had at least one brand-specific transaction during the holdout

6. **Compute metrics** — Shop Rate, Spend Rate, Avg Ticket, and Avg Transactions per Shopper

Brand Matching Logic

Brand transactions are identified by matching keywords (case-insensitive) against three columns in the transaction data:

- `BRAND_NAME`
- `STORE_NAME`
- `MERCHANT_DESCRIPTION`

For example, to identify ActBlue transactions, the keyword `ACTBLUE` is matched against all three columns. Multiple keywords per brand are supported and OR'd together.

Audiences Under Validation

The following audiences are configured for validation. They span two brands — **ActBlue** and **Ross** — and include both known-shopper seeds and lookalike expansions for each.

ActBlue Audiences

#	Audience Name	Type	Audience ID
1	ActBlue Exposed Likely Prospects	Propensity / Prospects	`akkio_audience_a64a3518_0b98_428d_bd52_62193f77927b`
2	ActBlue Control Likely Prospects Lookalike	Lookalike Expansion	`akkio_audience_4213278e_2935_4131_a114_df8976f47fbb`
3	ActBlue Shoppers Exposed	Known Shoppers (Seed)	`akkio_audience_cf577ee6_08db_4294_9716_bbf06b7c389b`

#	Audience Name	Type	Audience ID
4	ActBlue Shoppers Exposed Lookalike	Lookalike Expansion	`akkio_audience_9588a38d_8d82_4c7a_87b5_05299c694f6d`

ActBlue audience pairs:

- **Shoppers Exposed** (seed of known ActBlue buyers) paired with its **Shoppers Exposed Lookalike** (expansion audience modeled from the seed). Comparing these two shows how well the lookalike retains the purchase signal of the original seed.
- **Exposed Likely Prospects** (propensity-scored prospects) paired with the **Control Likely Prospects Lookalike** (a broader lookalike built from the prospects pool). Comparing these two shows how targeted prospect scoring compares to broader lookalike expansion.

Ross Audiences

#	Audience Name	Type	Audience ID
5	Ross Likely Buyers	Propensity / Prospects	`akkio_audience_ab2b535c_3a4b_4a41_94b0_df0564f7a4c7`
6	Ross Likely Buyers Lookalike	Lookalike Expansion	`akkio_audience_b5ecc926_f421_4be2_acdf_e672c6d77c7a`
7	Ross Shoppers Exposed Non-Holiday	Known Shoppers (Seed)	`akkio_audience_62341a69_d801_487f_817b_a6a224f64f5b`
8	Ross Shoppers Exposed Non-Holiday Lookalike	Lookalike Expansion	`akkio_audience_1b2a8c56_c952_465b_a41e_1220e97a982e`

Ross audience pairs:

- **Shoppers Exposed Non-Holiday** (seed of known Ross buyers, excluding holiday-driven purchases) paired with its **Non-Holiday Lookalike**. The "non-holiday" filter ensures the seed captures habitual Ross shoppers rather than one-time holiday gift buyers, providing a cleaner behavioral signal.
- **Likely Buyers** (propensity-scored prospects) paired with the **Likely Buyers Lookalike**. Demonstrates how the scoring model identifies high-value prospects compared to a broader expansion.

Validation Results

The table below shows the holdout validation results for all eight audiences. The holdout window is **September 1 – September 30, 2025**.

ActBlue Results

Metric	Exposed Likely Prospects	Control Likely Prospects LAL	Shoppers Exposed (Seed)	Shoppers Exposed LAL
Total Audience IDs	100,000	1,562,040	28,177	704,692
Active Matched IDs	99,578	208,938	26,636	74,854
Brand Shoppers	1,967	2,464	3,594	3,785
Brand Transactions	6,112	7,626	12,669	13,042
Brand Spend	$346,064.70	$394,588.69	$315,304.18	$326,642.82
Shop Rate	**1.98%**	**1.18%**	**13.49%**	**5.06%**
Spend Rate	**$3.48**	**$1.89**	**$11.84**	**$4.36**
Avg Ticket	$56.62	$51.74	$24.89	$25.05

Metric	Exposed Likely Prospects	Control Likely Prospects LAL	Shoppers Exposed (Seed)	Shoppers Exposed LAL
Avg Trans / Shopper	3.11	3.09	3.53	3.45

Key observations — ActBlue:

- **Shoppers Exposed (Seed)** achieves the highest shop rate at 13.49%, as expected — these are known ActBlue buyers, so the high holdout conversion reflects strong retention behavior.
- **Shoppers Exposed Lookalike** retains meaningful signal at 5.06% shop rate, demonstrating that the lookalike model successfully identifies individuals with ActBlue purchase propensity beyond the seed.
- **Exposed Likely Prospects** shows a 1.98% shop rate — nearly **1.7x higher** than the broader Control Likely Prospects Lookalike (1.18%), indicating that targeted prospect scoring meaningfully outperforms broader lookalike expansion.
- Avg Ticket is notably higher for the prospect audiences (52–57) vs. the shopper-based audiences ($25), suggesting prospects who convert tend to make larger individual donations.

Ross Results

Metric	Likely Buyers	Likely Buyers LAL	Shoppers Exposed Non-Holiday (Seed)	Shoppers Exposed Non-Holiday LAL
Total Audience IDs	597,559	1,019,936	437,060	519,377
Active Matched IDs	508,450	539,309	403,536	409,969
Brand Shoppers	6,567	8,298	68,307	68,781
Brand Transactions	7,715	10,363	110,043	110,787
Brand Spend	$523,796.10	$695,379.87	$7,441,313.20	$7,486,946.90
Shop Rate	**1.29%**	**1.54%**	**16.93%**	**16.78%**

Metric	Likely Buyers	Likely Buyers LAL	Shoppers Exposed Non-Holiday (Seed)	Shoppers Exposed Non-Holiday LAL
Spend Rate	**$1.03**	**$1.29**	**$18.44**	**$18.26**
Avg Ticket	$67.89	$67.10	$67.62	$67.58
Avg Trans / Shopper	1.17	1.25	1.61	1.61

Key observations — Ross:

- **Shoppers Exposed Non-Holiday (Seed)** delivers a 16.93% shop rate — very strong retention, confirming that non-holiday Ross buyers are highly habitual repeat shoppers.
- **Shoppers Exposed Non-Holiday Lookalike** performs almost identically (16.78%), indicating that the Ross shopping behavior is broadly distributed and the lookalike captures a population with very similar purchase patterns to the seed.
- **Likely Buyers** and **Likely Buyers Lookalike** show lower but comparable shop rates (1.29% vs. 1.54%), which is expected for prospect/acquisition audiences.
- Avg Ticket is remarkably consistent across all Ross audiences (~67–68), reflecting the stable price-point nature of Ross's retail model.
- Avg Transactions per Shopper is notably lower for Ross (1.2–1.6) vs. ActBlue (3.1–3.5), consistent with the difference between monthly retail shopping and recurring political donation behavior.

How to Interpret These Results

Shop Rate Is the Primary Quality Signal

Shop Rate answers the core question: "*What percentage of active audience members actually purchased from the brand during the holdout window?*"

- **Higher shop rate = better audience quality** — the audience is more concentrated with likely buyers
- **Seed audiences will always have higher shop rates** — they are built from known buyers, so holdout shop rate measures retention, not prediction

- **Lookalike / propensity audiences are the true test** — their shop rate reflects the model's ability to identify *new* buyers

Spend Rate Captures Dollar-Value Impact

Spend Rate combines shop rate with purchase value to answer: "*How much brand revenue does each active audience member represent?*"

This is the most actionable metric for media planning — it directly translates audience quality to economic value.

Lift Over Baseline

To contextualize these results, compare against a **random baseline** — the shop rate you would observe by taking a random sample of the same size from the active population. Any audience's shop rate divided by the baseline shop rate gives you **lift**:

```
Lift = Audience Shop Rate / Random Baseline Shop Rate
```

A lift of 2.0x means the audience is twice as likely to contain brand shoppers as a random sample. Higher lift = better targeting precision.

Automation & Reproducibility

Configuration-Driven Validation

All audiences are defined in a single YAML configuration file (`audiences.yml`), making it easy to add, remove, or modify audiences without changing code:

```yaml
defaults:
  date_start: "2025-09-01"    # Holdout start (inclusive)
  date_end: "2025-10-01"      # Holdout end (exclusive)

audiences:
  - audience_id: "akkio_audience_a64a3518_..."
    name: "ActBlue Exposed Likely Prospects"
    brand_keywords:
      - "ACTBLUE"

  - audience_id: "akkio_audience_ab2b535c_..."
    name: "Ross Likely Buyers"
    brand_keywords:
      - "ROSS"
```

Each audience entry specifies:

- **audience_id** — the unique Akkio audience identifier (links to `AUDIENCE_LOOKUP`)
- **name** — a human-readable label for reporting
- **brand_keywords** — one or more keywords matched case-insensitively against `BRAND_NAME` , `STORE_NAME` , and `MERCHANT_DESCRIPTION`

Global defaults (holdout window dates, database/schema) can be overridden per audience.

Execution

The validation is executed via a Python script that:

1. Reads the audience configuration from `audiences.yml`
2. Connects to Snowflake (credentials from environment variables or dbt profiles)
3. Runs a parameterized validation query for each audience against the holdout window
4. Aggregates all results into a summary table
5. Exports results to CSV for further analysis

```
python analyses/audience_validation/audience_validation.py
```

Results are written to `analyses/audience_validation/output/audience_validation_results.csv` .

Validated SQL Query

The core validation query executed for each audience is shown below. It follows the same pattern for every audience — only the audience ID, brand keywords, and date range change.

```sql
WITH AUDIENCE AS (
  SELECT AKKIO_ID
  FROM AUDIENCE_LOOKUP
  WHERE audience_id = '<audience_id>'
    AND ver = (
      SELECT MAX(ver)
      FROM AUDIENCE_METADATA
      WHERE audience_id = '<audience_id>'
    )
),
TOTAL_LAL AS (
  SELECT COUNT(DISTINCT AKKIO_ID) AS TOTAL_LAL_IDS
  FROM AUDIENCE
),
ACTIVE_MATCHED AS (
  SELECT COUNT(DISTINCT A.AKKIO_ID) AS ACTIVE_MATCHED_IDS
  FROM AUDIENCE AS A
  INNER JOIN FACT_TRANSACTION_ENRICHED AS F
    ON A.AKKIO_ID = F.AKKIO_ID
  WHERE F.TRANS_DATE >= '<date_start>'
    AND F.TRANS_DATE <  '<date_end>'
),
BRAND_METRICS AS (
  SELECT
    COUNT(DISTINCT A.AKKIO_ID) AS BRAND_SHOPPERS,
    COUNT(F.TXID)              AS BRAND_TRANSACTIONS,
    SUM(F.TRANS_AMOUNT)        AS BRAND_SPEND
  FROM AUDIENCE AS A
  INNER JOIN FACT_TRANSACTION_ENRICHED AS F
    ON A.AKKIO_ID = F.AKKIO_ID
  WHERE F.TRANS_DATE >= '<date_start>'
    AND F.TRANS_DATE <  '<date_end>'
    AND (
      UPPER(F.BRAND_NAME)            LIKE '%<KEYWORD>%'
      OR UPPER(F.STORE_NAME)         LIKE '%<KEYWORD>%'
      OR UPPER(F.MERCHANT_DESCRIPTION) LIKE '%<KEYWORD>%'
    )
)
SELECT
  T.TOTAL_LAL_IDS          AS "Total Audience IDs",
  A.ACTIVE_MATCHED_IDS     AS "Active Matched IDs",
  B.BRAND_SHOPPERS         AS "Brand Shoppers",
  B.BRAND_TRANSACTIONS     AS "Brand Transactions",
```

```sql
  B.BRAND_SPEND             AS "Brand Spend",
  B.BRAND_SHOPPERS / A.ACTIVE_MATCHED_IDS  AS "Shop Rate",
  B.BRAND_SPEND   / A.ACTIVE_MATCHED_IDS  AS "Spend Rate",
  B.BRAND_SPEND   / B.BRAND_TRANSACTIONS   AS "Avg Ticket",
  B.BRAND_TRANSACTIONS / B.BRAND_SHOPPERS  AS "Avg Trans / Shopper"
FROM TOTAL_LAL   AS T
CROSS JOIN ACTIVE_MATCHED AS A
CROSS JOIN BRAND_METRICS  AS B;
```

Critical rules enforced in every query:

- Only transactions within the holdout window are counted
- The denominator for Shop Rate and Spend Rate is **Active Matched IDs** (audience members with any transaction in the holdout), not total audience size
- Brand matching uses case-insensitive LIKE across three columns
- The latest audience version is always used (`MAX(ver)` from `AUDIENCE_METADATA`)

Summary

The audience validation framework provides a rigorous, transparent method for measuring audience quality:

1. **Temporal holdout design** prevents data leakage and ensures metrics reflect true predictive power
2. **Standardized metrics** (Shop Rate, Spend Rate, Avg Ticket) enable direct comparison across audiences, brands, and modeling approaches
3. **Active Matched IDs denominator** ensures fair comparison regardless of panel coverage differences
4. **Configuration-driven automation** makes it easy to add new audiences and re-run validation as new data becomes available
5. **Seed + Lookalike pairing** separates retention measurement from acquisition prediction, providing a complete picture of audience value

This framework can be extended to any brand or merchant available in the transaction data, and to any audience construction methodology — enabling ongoing benchmarking and optimization of audience quality over time.