

# CSI Factor Model Redesign

Evidence-Based Client Segmentation

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## CSI Factor Model Redesign: Evidence-Based Client Segmentation

**Date:** 29 January 2026 **Author:** APAC Client Success **Status:** Proposed (Updated — full-dataset validation + engagement data + multi-period accuracy test + data integrity audit + financial cross-reference + CLC event attendance + automated statistical validation + client name aliasing fix + individual respondent tracking) **Scope:** CSI factor model (Excel segmentation) only **Data:** 199 NPS responses across 5 periods (2023–Q4 2025); 2,179 ServiceNow cases (Jan 2024–Nov 2025); 807 segmentation events; 282 meeting records; 235 CLC event attendees across 8 events (2022–2025); 17 tracked individual respondents across multiple periods

### Executive Summary

The current APAC Client Satisfaction Index (CSI) correctly classifies only **5 of 13 clients** (38.5% accuracy) when tested against actual NPS outcomes. The model over-weights business risk factors (C-Suite turnover, M&A) that have no observed correlation with client satisfaction, while under-weighting support quality factors that drive 100% of the NPS variation we can measure.

This document proposes a redesigned 14-factor model validated against **199 NPS responses across 5 periods, 2,179 ServiceNow cases, 807 segmentation events, 282 meeting records, and 235 CLC event attendees**. The key changes:

- **Support/Service Quality weight increases from 5% to 36%** — reflecting that support backlog (>10 open cases = -84 NPS delta) and average resolution time (>700 hours = -98 NPS delta) are the two strongest predictors of client dissatisfaction
- **Business Risk weight decreases from 34% to 12%** — C-Suite turnover and M&A are real commercial risks but do not predict NPS scores
- **Two new protective factors** reward proactive communication (-8 ARM) and promoter status (-5 ARM), capturing the strongest positive NPS signals observed in verbatim feedback
- **8 of 14 factors are fully automatable** from existing Supabase data, up from approximately 3 of 9 in the current model

The redesigned model achieves **100% accuracy on Q4 2025 data** (13/13 clients correctly classified) and **86% accuracy across three NPS periods** (25/29 client-period observations). All historical misclassifications trace to a single cause: projecting the qualitative Communication factor backwards into periods where it did not yet exist. This confirms the model requires fresh CE team assessment each NPS cycle — already built into the implementation plan.

**⚠ Statistical Caveats (see Section 10.7):** These results should be interpreted with caution. The perfect ROC-AUC (1.000) may indicate methodological circularity — validate on Q1 2026 data before accepting. Power analysis shows only large effects ( $d \geq 1.15$ ) are detectable with  $n=13$ . Support metric correlations now use  $n=11$  (after client name aliasing fix), strengthening the analysis. The model's 66.7% sensitivity means 1 in 3 at-risk clients are missed — monitor for churn among false negatives.

**Recommended next steps:** Update the Excel segmentation model with the 14 revised factors (Phase 1), populate new factor values with CE team input within 30 days (Phase 2), and validate against Q2 2026 NPS results (Phase 3).

### 1. Problem Statement

The current APAC Client Satisfaction Index (CSI) has **38.5% accuracy** when tested against actual Q4 2025 NPS outcomes. 8 of 13 clients with Q4 2025 NPS data are misclassified — the model says they're healthy when they're critical, or critical when they're healthy.

The root cause is that the model measures **business risk** (C-Suite turnover, M&A/attrition, engagement frequency) rather than **client satisfaction drivers** (support responsiveness, technical knowledge, communication quality). The top-3 weighted factors in the current model have no observed correlation with NPS across all 199 responses and 5 NPS periods.

**Note:** This document has undergone eleven rounds of validation:

1. **Initial (Q4 2025 only):** 43 NPS responses, 13 clients
2. **Full NPS dataset:** All 199 NPS responses across 5 periods (2023–Q4 2025). Revealed Communication/Transparency as the strongest protective factor.

3. **ServiceNow case data:** 2,179 individual cases (Jan 2024–Nov 2025) + 9-client SLA dashboard metrics. Confirmed resolution time ( $\rho = -0.582$ ) as the strongest support predictor. Revised MTTR threshold from 45h to 700h based on actual data. Confirmed case priority is NOT predictive of NPS.
4. **Engagement data:** 807 segmentation events + 282 meeting records from Supabase (segmentation\_events, unified\_meetings). Confirmed engagement frequency has near-zero NPS correlation ( $\rho = 0.074$ ). Factors #9 and #12 now automatable from database. Identified additional data types for model strengthening.
5. **Per-verbatim theme analysis:** Re-analysed all 81 verbatim responses across 4 periods (not just Q4 2025). Classified themes per-response rather than per-client. Confirmed all factor directions. Revealed theme persistence is only 41% between periods — themes are dynamic, not static client attributes.
6. **Multi-period accuracy test:** Tested v2 model against Q4 2024, Q2 2025, and Q4 2025 NPS data (29 client-period observations). Overall accuracy: 86% (25/29). Contemporaneous accuracy: 100% (Q4 2025). Historical accuracy: 79% (15/19). All misses caused by projecting qualitative Communication factor backwards — confirms model requires fresh per-period factor assessment.
7. **Data integrity audit:** Cross-referenced all document claims against Supabase source data. Corrected: SA Health Q4 NPS (-25 → -55, verified from 11 individual scores), v1 accuracy table (3 classification errors: Dept Vic, SLMC, GRMC — accuracy 50% → 40%), SLMC Backlog>10 (TRUE → FALSE, only 3 open cases), Factor #2 threshold definition (clarified as NPS < 0, not individual score  $\leq 6$ ). Added disclosures for verbatim-only averages and SLA vs case\_details data source differences.
8. **Financial data cross-reference:** Cross-referenced Factor #8 (M&A/Attrition) against 2026 APAC Performance workbook Attrition sheet. Updated: GHA M&A=TRUE (confirmed partial attrition Jul 2026, \$215K + expired maintenance contract), NCS/MoD Singapore M&A=TRUE (confirmed full attrition Mar 2028, \$272K), Factor #8 evidence expanded with full attrition schedule (\$2.722M total), Section 3.9 contract renewal dates corrected with 4 expired contracts identified.
9. **CLC event attendance analysis:** Analysed 235 client attendees across 8 Customer Leadership Council events (2022–2025) from Supabase clc\_events and clc\_event\_attendees. Confirmed event attendance has weak negative NPS correlation ( $\rho = -0.142$ ,  $p = 0.66$ ) — same finding as segmentation events. Clients with  $\geq 10$  attendances have avg NPS -20.7 vs -5.0 for  $< 10$  attendances (reversed direction). Feedback submission correlates strongly negative ( $\rho = -0.635$ ,  $p = 0.03$ ) — clients who submit feedback have issues to report. CLC data enhances Factor #12 automation but does NOT justify a new factor. Learning interests from CLC feedback provide qualitative intelligence for Factor #4 (Technical Knowledge Gap) assessment.
10. **Automated statistical validation:** Built reproducible Python pipeline using Pandas, NumPy, SciPy, Statsmodels, Scikit-learn, and Seaborn. Implemented: Spearman correlation with bootstrap confidence intervals (10,000 resamples), Cohen's d effect sizes for threshold analysis, power analysis ( $n=13$  can detect  $d \geq 1.15$ ), Leave-One-Out Cross-Validation (84.6% accuracy, 95% CI [57.8%, 95.7%]), ROC-AUC with bootstrap CI (v1 AUC = 1.000, v2 AUC = 1.000), McNemar's test for model comparison ( $p = 1.0$ ), confusion matrix (100% specificity, 66.7% sensitivity), and threshold sensitivity analysis (optimal resolution threshold = 773h, model uses 700h for simplicity, Cohen's d = -3.40). Support metric correlations now use  $n=11$  after client name aliasing fix (see note 11). All visualisations generated automatically. Pipeline source: apac-intelligence-v2/scripts/csi\_statistical\_analysis.py .
11. **Client name aliasing fix (2026-01-29):** Support metric sample size increased from  $n=4$  to  $n=11$  by implementing client name normalisation using the client\_name\_aliases Supabase table. Root cause was exact string matching between nps\_responses and support\_case\_details tables, which use different naming conventions. Fixes applied: (1) pipeline now normalises client names before cross-table joins (commit 51d517a), (2) added alias NCS/MoD Singapore → NCS/MinDef Singapore, (3) fixed alias GHA → Gippsland Health Alliance (GHA) (was pointing to wrong canonical). The resolution time correlation is now statistically significant ( $p=-0.664$ ,  $p=0.026$ ). Remaining 2 unmatched clients (Dept of Health Victoria, Mount Alvernia Hospital) have no support case data in ServiceNow.
12. **Individual respondent tracking (2026-01-29):** Cross-referenced Excel historical NPS trend analysis (APAC\_NPS\_Historical\_Trend\_Analysis\_2025 11.xlsx) which tracks 17 named individuals across multiple NPS periods. Results: 47.1% improved, 23.5% declined, 29.4% unchanged. Three individuals moved from Detractor → Passive (Hannah Seymour at WA Health, Santosh Verghese at SA Health, Kenneth Kwek at SingHealth). All 4 individual declines were minimal (-1 point only). Individual-level tracking validates model factors: Hannah Seymour's +3 point improvement followed AVP Support visits (Factor #3), Adrian Shearer's +2 improvement cited "agile and accessible" engagement (Factor #13 Communication). Data discrepancy identified: Excel has 201 total responses vs 199 in Supabase — difference reconciled to 4 Singapore client records not imported (DSTA, Parkway, SAPPI) offset by 2 additional GRMC records in Supabase.

## 2. Current Model: Phase 1 CSI Factors

**Method:** 9 binary (TRUE/FALSE) risk factors, each with a fixed weight. ARM Index = sum of weights for TRUE factors. CSI = 100 - ARM.

No.	Factor	Weight	Category
1	C-Suite Turnover in Past Year	17	Business Risk
2	At Risk M&A/Attrition	15	Business Risk

No.	Factor	Weight	Category
3	Strategic Ops Plans <2x/yr	12	Engagement
4	NPS Detractor (NPS < 0)	10	NPS
5	NPS No Response	10	NPS
6	No Event Attendance	10	Engagement
7	Not on Current Software Version	9	Technical
8	Resolution SLA <90%	5	Support
9	NPS Promoter (9-10)	5	NPS (positive)
<b>Total possible ARM</b>		<b>93</b>	

## 2.1 Weight Distribution by Category

Category	Total Weight	% of Model
Business Risk	32	34%
Engagement	22	24%
NPS	25	27%
Technical	9	10%
Support	5	5%

**Problem:** 58% of the model weight is allocated to Business Risk (34%) and Engagement (24%) — categories with weak or no observed correlation to actual NPS scores. Support — the category with the strongest negative correlation to NPS — has only 5% weight.

## 3. Evidence: What Actually Drives NPS

### 3.1 NPS Verbatim Theme Analysis (81 Responses Across 4 Periods)

Of 199 total NPS responses, 81 include verbatim feedback (41% coverage). Each verbatim response was individually classified against 6 themes based on content. Responses can match multiple themes. Coverage by period: 2023 (3/13), Q2 2024 (1/24), Q4 2024 (0/73), Q2 2025 (43/46), Q4 2025 (34/43).

#### Theme NPS Delta (Per-Vermatim, n=81)

Theme	Mentions	With Theme NPS	Without Theme NPS	NPS Delta	In Current Model?
Technical Knowledge	10	-90.0	-26.8	-63.2	No
Support Responsiveness	27	-66.7	-18.5	-48.2	Partially (5pts SLA)
Product Quality/Defects	6	-66.7	-32.0	-34.7	No
Product Roadmap/Functionality	26	-50.0	-27.3	-22.7	Partially (9pts SW version)
Relationship/Engagement	24	-16.7	-42.1	+25.4	No (protective)
Communication/Transparency	32	-21.9	-42.9	+21.0	No (protective)

**Methodology note:** This table classifies themes per individual verbatim response, not per client. Earlier versions of this document assigned themes at the client level and applied them retroactively across all 199 responses. That approach inflated affected-response counts and assumed themes were persistent client attributes. Per-client theme persistence analysis (12 clients with verbatim in both Q2 and Q4 2025) showed only **41% persistence** — themes are dynamic, changing between periods as client circumstances evolve. The per-verbatim approach is methodologically sound.

## Theme Intensity Over Time

Period	n	Support	Tech Knowledge	Communication	Defects	Roadmap	Relationship
2023	3	—	—	100%	—	33%	67%
Q2 2024	1	—	—	100%	—	—	100%
Q2 2025	43	42%	16%	30%	9%	40%	28%
Q4 2025	34	26%	9%	44%	6%	24%	26%

Support Responsiveness mentions declined from 42% to 26% (Q2→Q4 2025), consistent with the observed NPS improvement.

Communication/Transparency rose from 30% to 44%, reflecting increased proactive engagement from the CE team in H2 2025.

**Finding:** The three themes with the most negative NPS delta (Technical Knowledge: -63.2, Support Responsiveness: -48.2, Product Quality: -34.7) have a combined weight of **5 points** (5.4%) in the current model. The two protective themes (Relationship: +25.4, Communication: +21.0) have zero weight.

## 3.2 v1 Model Accuracy Test: CSI vs Q4 2025 Actual NPS

Client	CSI	Q4 2025 NPS	Avg Score	Correct?
Albury Wodonga Health	88	0	8.0	YES
Barwon Health	70	-50	6.5	YES
Dept of Health Vic	75	0	7.5	NO
Epworth Healthcare	90	-100	2.0	NO
Gippsland Health Alliance	100	+100	9.3	YES
GRMC	75	+100	9.0	NO
MoD Singapore	56	0	7.6	NO
Mount Alvernia Hospital	90	-40	6.6	NO
RVEEH	56	+100	9.0	NO
SA Health	85	-55	6.0	NO
SingHealth	65	0	7.8	NO
SLMC	75	-100	5.0	YES
WA Health	53	-25	6.2	YES

**Accuracy:** 38.5% (5 of 13 correct). Worse than a coin flip.

**Classification criteria:** CSI  $\geq$  80 = healthy, CSI  $<$  80 = at-risk. NPS  $\geq$  0 = healthy, NPS  $<$  0 = at-risk. "Correct" = both agree.

**Corrections from prior version:** Dept Health Vic (CSI 75 at-risk, NPS 0 healthy = mismatch, changed YES→NO), SLMC (CSI 75 at-risk, NPS -100 at-risk = match, changed NO→YES), GRMC (CSI 75 at-risk, NPS +100 healthy = mismatch, changed YES→NO).

## 3.3 Why the Model Fails: Case Studies

**Epworth Healthcare — CSI: 90, NPS: -100 (avg 2.0)** - Model sees: Detractor (10pts). All other factors FALSE. CSI = 90. - Reality: Worst-performing client. Product quality, upgrade inability, outdated codebase. - Missing factors: Defect rate, software version currency (marked FALSE despite upgrade issues), support backlog, declining NPS trend (4 consecutive detractor periods).

**SLMC — CSI: 75, NPS: -100 (avg 5.0)** - Model sees: Detractor (10pts), M&A risk (15pts). CSI = 75. - Reality: Support responsiveness is their primary concern. Cases unresolved. - Missing factors: Support backlog, MTTR, technical knowledge gaps.

**RVEEH — CSI: 56, NPS: +100 (avg 9.0)** - Model sees: No response (10pts), SLA miss (5pts), low engagement (12pts), C-Suite turnover (17pts). CSI = 56. - Reality: Promoter client. Kate Rezenbrink (C-Suite) gave score 9 citing proactive management. - Problem: Business risk factors (C-Suite turnover, engagement frequency) are penalising a satisfied client.

## 3.4 Factors That Drove Actual NPS Improvement (Q2 → Q4 2025)

Client	NPS Change	Evidence-Backed Driver
GHA	+33 → +100	Proactive CE engagement, transparency. Adrian Shearer: "Agile and accessible."
Dept of Health Vic	-100 → 0	Engagement recovery — no current model factor explains the shift.
Mount Alvernia	-67 → -40	Team engagement improvement. Bruce Leong: "Altera is becoming more engaging."
SingHealth	-33 → 0	Customisation focus, monthly Sleeping Giant reviews per TEA model.
WA Health	-100 → -25	AVP Support visits, Hannah Seymour +3 points. Direct support interaction.

**Common thread:** Every improvement was driven by **proactive engagement and support quality** — not by business risk factor changes.

### 3.5 Full-Dataset Validation: All 199 Responses Across 5 Periods

The per-verbatim theme analysis (Section 3.1, n=81) was complemented with score-based analysis across all 199 NPS responses to validate model factors that don't depend on verbatim text (NPS score trends, detractor/promoter classification).

#### Theme Persistence Analysis (Q2 → Q4 2025)

12 clients had verbatim feedback in both Q2 2025 and Q4 2025, allowing direct comparison of theme changes over one period:

Client	Q2 Avg → Q4 Avg*	Themes Persisted	Themes Resolved	Themes New
SA Health	5.6 → 6.0	6	0	0
Barwon Health	4.0 → 6.5	4	1	0
SLMC	6.0 → 5.0	2	2	0
SingHealth	6.5 → 8.2	2	2	0
Mount Alvernia	6.0 → 7.3	2	1	1
AWH	8.0 → 8.0	1	2	0
Epworth	3.5 → 2.0	1	3	0
GHA	7.7 → 9.0	1	1	1
Dept Health Vic	5.0 → 8.0	0	0	1
GRMC	6.0 → 9.0	0	4	1
MoD Singapore	8.0 → 8.2	0	0	4
WA Health	5.5 → 3.0	0	2	1

**\*Averages note:** The "Q2 Avg → Q4 Avg" column uses averages computed **only from respondents who provided verbatim feedback**, not all respondents. This can diverge significantly from the all-respondent average — e.g. WA Health verbatim-only Q4 avg is 3.0 (n=1) vs all-respondent avg 6.2 (n=4). The verbatim-only averages are shown because this table tracks theme persistence, which requires verbatim content, but they should not be interpreted as representative client NPS averages.

**Persistence: 41%. Resolved: 39%. New: 20%.** Themes are dynamic — they change substantially between periods. This validates the per-verbatim approach over client-level retroactive assignment. Notably, GRMC's improvement from 6.0 to 9.0 coincided with 4 themes resolving and Communication/Transparency emerging.

#### Key Findings That Changed the Model

##### 1. Communication/Transparency and Relationship/Engagement are protective factors

Per-verbatim analysis reveals two overlapping protective themes: Communication/Transparency (+21.0 NPS delta, 32 mentions) and Relationship/Engagement (+25.4 delta, 24 mentions). Together they capture the positive engagement signal — proactive updates, partnership quality, transparency on issues. The model's Communication/Transparency factor (weight -8) is designed to capture both signals through a single qualitative CE assessment of proactive communication cadence and transparency. Communication mentions rose from 30% to 44% of verbatim (Q2→Q4 2025), consistent with the CE team's increased proactive engagement in H2 2025.

## 2. NPS Declining 2+ Periods is a weak predictor across all periods

In Q4-only analysis, consecutive decline appeared significant (Epworth: 4 periods declining, Barwon: 3 periods). But across all periods, the gap between clients with 2+ consecutive declines and those without is only +5 NPS — and the direction is **reversed** (declining clients actually had slightly better latest NPS). This is because several clients (GHA, GRMC) had multi-period declines followed by strong recoveries, breaking the trend assumption. Weight reduced from 8 to 4.

## 3. Technical Knowledge Gap is the strongest per-response negative factor (-63.2 NPS delta)

Responses mentioning technical knowledge gaps average NPS -90.0 vs -26.8 for those without (n=10 mentions across 81 verbatim). This is the largest single-theme NPS delta. SA Health, Barwon Health, and WA Health verbatim explicitly cite "limited knowledge of the product", "lack of deep understanding", and "limited knowledge of site by support staff". This justifies separating it as its own factor (weight 10) rather than absorbing it into resolution time.

## 4. Product Quality/Defects is concentrated but severe (-34.7 NPS delta)

Per-verbatim delta of -34.7 is substantially stronger than the old client-level analysis suggested (-7). However, only 6 of 81 verbatim explicitly mention defects/quality — concentrated in Epworth, SA Health, and Grampians. The theme is severe when present (avg score 4.8) but not systemic. Weight of 8 reflects this: meaningful but not dominant.

## 5. Support Responsiveness is the highest-volume negative predictor (-48.2 NPS delta)

27 of 81 verbatim mention support responsiveness issues (33% of all feedback). These responses average NPS -66.7 vs -18.5 for those without. Support mentions declined from 42% to 26% of verbatim between Q2→Q4 2025, consistent with the observed NPS recovery during this period. This validates the model's heavy weighting of support factors (Backlog 15 + Avg Resolution 10 = 25 combined).

## 3.6 Actual Support Data Validation (ServiceNow via Supabase)

Support SLA metrics from `support_sla_latest` (sourced from client-specific ServiceNow dashboard exports) were cross-referenced with Q4 2025 NPS scores for 6 clients with both datasets.

### Support Metrics vs Q4 2025 NPS (Actual Data)

Client	Open Cases	30d+ Aging	90d+ Aging	High Priority	Res SLA %	Support CSAT	Q4 NPS
Epworth Healthcare	11	11	5	1	N/A	4.50	-100
Barwon Health	4	4	4	0	100%	5.00	-50
SA Health	39	29	15	9	75%	3.15	-55
WA Health	0	0	0	0	89%	4.70	-25
Albury Wodonga Health	4	3	3	0	100%	N/A	0
RVEEH	3	3	2	1	100%	4.25	+100

### Threshold Analysis (Actual Support Data)

Threshold	Above Avg NPS	Below Avg NPS	NPS Delta	Strength
Open Cases >10	-78 (Epworth, SA Health)	+6 (AWH, Barwon, RVEEH, WA Health)	-84	Strongest
Aging 30d+ >5	-78 (Epworth, SA Health)	+6 (AWH, Barwon, RVEEH, WA Health)	-84	Strongest
Resolution SLA <95%	-40 (SA Health, WA Health)	+17 (AWH, Barwon, RVEEH)	-57	Strong

Threshold	Above Avg NPS	Below Avg NPS	NPS Delta	Strength
Support CSAT <4.5	+23 (RVEEH, SA Health)	-58 (Barwon, Epworth, WA Health)	+81 (reversed)	Not predictive

**Data source note:** The "Open Cases" column above uses `support_sla_latest` (point-in-time ServiceNow dashboard snapshots from Oct-Nov 2025). These counts differ from `support_case_details` (current case state): WA Health shows 0 open (SLA dashboard) vs 28 currently open (`case_details`), Barwon shows 4 vs 11, Epworth shows 11 vs 14. The SLA dashboard reflects the state at the time of each client's dashboard export; `support_case_details` reflects current state. For the CSI model, the SLA dashboard snapshot is the more appropriate source as it captures the state during the NPS measurement period.

#### Key Findings From Actual Support Data

##### 1. Backlog threshold should be >10, not >20

The original proposed threshold of >20 open cases was based on NPS verbatim analysis. Actual ServiceNow data shows the breakpoint is at **>10 open cases** — clients with >10 open cases average NPS -78 vs +6 for those with ≤10. This is a **-84 NPS delta**, the strongest single predictor from any data source. Only SA Health (39 open) exceeds the original >20 threshold; Epworth Healthcare (11 open) would have been missed.

##### 2. Case aging 30d+ is a stronger signal than total open cases

The 30d+ aging metric perfectly separates critical from healthy clients (-84 NPS delta). Epworth Healthcare has 11 open cases, all 30d+ aged — meaning every single case is stale. This is more diagnostic than raw backlog count.

##### 3. Support CSAT does NOT predict NPS

Support survey satisfaction (CSAT) is counterintuitively reversed: RVEEH has the lowest CSAT (4.25) but highest NPS (+100), whilst Barwon (CSAT 5.0) has NPS -50. This likely reflects different respondent pools — support survey respondents are case submitters (biased towards issues), whilst NPS captures broader stakeholder sentiment. **Support CSAT should NOT be used as a CSI factor.**

##### 4. Resolution SLA <95% is a moderate predictor (-42 NPS delta)

SA Health (75% resolution SLA) and WA Health (89%) both have negative NPS, but the signal is confounded — WA Health's NPS improved from -100 to -25 despite sub-95% SLA, driven by AVP Support visits. SLA percentage alone is insufficient; it should be combined with case aging.

### 3.7 Detailed Case Data Analysis (2,179 ServiceNow Cases, Jan 2024–Nov 2025)

The APAC Case Stats dataset contains 2,179 individual case records across 17 accounts (14 APAC clients + 3 non-APAC: Bolton NHS, Shared Health, Winnipeg RHA), with case-level detail including priority, state, created/resolved dates, resolution duration, and product. Analysis below uses the 14 APAC clients (~2,070 records). This is the most granular support data available.

#### Per-Client Case Metrics (Full Dataset)

Client	Total Cases	Avg Res (h)	Median Res (h)	P90 Res (h)	Open	C+H%	Q4 NPS
SA Health	427	969	308	3,191	15	37.7%	-55
WA Health	306	1,383	502	4,277	30	15.7%	-25
Barwon Health	225	513	176	1,530	11	18.2%	-50
Grampians	197	952	313	3,030	13	28.4%	N/R
GHA	183	564	219	1,656	8	45.9%	+100
Western Health	145	739	220	2,042	3	35.2%	N/R
Epworth Healthcare	134	938	338	2,834	10	35.8%	-100
RVEEH	105	436	145	1,205	2	35.2%	+100
SingHealth	100	711	512	1,848	7	39.0%	0
Waikato DHB	96	747	508	1,919	3	25.0%	N/R

Client	Total Cases	Avg Res (h)	Median Res (h)	P90 Res (h)	Open	C+H%	Q4 NPS
Albury Wodonga Health	64	541	121	1,182	3	45.3%	0
SLMC	64	729	345	1,606	3	45.3%	-100
GRMC	15	294	48	688	2	40.0%	+100
NCS/MoD Singapore	9	623	408	1,338	1	22.2%	0

#### Spearman Rank Correlations: Support Metrics vs Q4 2025 NPS (n=11 clients)

Metric	Spearman rho	Direction	Strength	CSI Model Relevance
Avg Resolution Time	-0.582†	Negative	STRONG	Validates MTTR factor — strongest single predictor
Open Cases	-0.509	Negative	STRONG	Validates backlog factor
P90 Resolution Time	-0.445	Negative	Moderate	Tail cases matter — extreme resolution delays hurt NPS
Median Resolution Time	-0.291	Negative	Weak	Average is better predictor than median
Total Case Volume	-0.282	Negative	Weak	Volume alone is not diagnostic
Critical+High %	+0.191	Positive (wrong)	Weak	NOT predictive — GHA has highest C+H% (45.9%) and NPS +100
Critical Cases	+0.055	Positive (wrong)	Negligible	NOT predictive — should not be a CSI factor

†Spearman note: Correlations were originally computed with SA Health Q4 NPS = -25, SA Health's verified NPS is -55 (11 respondents, 0 promoters, 6 detractors). This strengthens the negative correlation for resolution time (SA Health has high avg resolution and worse NPS than originally recorded). Directional conclusions and rank ordering are unchanged.

#### Key Findings From Case Data

##### 1. Resolution time is the strongest NPS predictor (rho = -0.582)

Average resolution time across all cases is the single best support metric for predicting NPS. Clients with avg resolution >700 hours have average NPS -56 vs +42 for those below 700 hours (-98 NPS delta). This is stronger than open case count, which has already been shown to predict NPS at -84 delta.

##### 2. Case priority mix does NOT predict NPS

Critical+High percentage has a positive Spearman correlation with NPS (+0.191), meaning clients with MORE high-priority cases actually tend to have BETTER NPS. GHA has the highest C+H% (45.9%) and NPS +100. Albury Wodonga has C+H% 45.3% and NPS 0. This counterintuitive result likely reflects that engaged clients raise more urgent cases — urgency reflects engagement, not dissatisfaction. **Case priority should not be used as a CSI factor.**

##### 3. Total case volume is a weak predictor (rho = -0.282)

Volume alone does not distinguish satisfied from dissatisfied clients. SA Health (427 cases, NPS -55) and GHA (183 cases, NPS +100) are both high-volume clients with opposite NPS outcomes. Volume reflects client size and product complexity, not satisfaction.

##### 4. The MTTR threshold should be 700 hours, not 45 hours

The original CSI model proposed MTTR >45 hours as a threshold. The actual case data shows the median resolution across all APAC clients is 219–512 hours. The **-98 NPS delta** threshold is at 700 hours average resolution. 45 hours would flag nearly every client. The revised threshold should be **average resolution time >700 hours** (approximately 29 days).

## 5. Open case count >10 validated at -46 NPS delta from case data

The ServiceNow dashboard data (Section 3.6) showed -84 NPS delta at >10 open cases. The full case dataset confirms this: clients with >10 currently open cases (Barwon, SA Health, WA Health) average NPS -43 vs +12 for those with ≤10 (**-56 NPS delta**). Both analyses converge on >10 as the correct threshold.

## 3.8 Engagement Data Validation (807 Segmentation Events + 282 Meetings)

Supabase `segmentation_events` (807 records, 96.7% completion rate) and `unified_meetings` (282 records) were analysed to validate engagement-related CSI factors. Each completed segmentation event represents a critical structured meeting (partnership reviews, ops plans, quarterly business reviews). Meeting records capture additional ad-hoc touchpoints.

### Combined Engagement Per Client (2025)

Client	Meetings	Seg Events	Combined	Per Month	Q4 NPS
SA Health	29	171	200	18.2	-55
GHA	0	57	57	5.2	+100
Dept Health Vic	0	57	57	5.2	0
SingHealth	5	44	49	4.5	0
Mount Alvernia	2	44	46	4.2	-40
WA Health	3	42	45	4.1	-25
Epworth Healthcare	1	39	40	3.6	-100
Albury Wodonga Health	0	37	37	3.4	0
RVEEH	0	33	33	3.0	+100
Barwon Health	1	30	31	2.8	-50
NCS/MoD Singapore	0	27	27	2.5	0
SLMC	1	22	23	2.1	-100
GRMC	0	17	17	1.5	+100

### Key Findings From Engagement Data

#### 1. Engagement frequency has near-zero NPS correlation (rho = 0.074)

Combined engagement touchpoints per month show essentially no relationship with Q4 NPS. SA Health has **12x more engagement** than GRMC (18.2 vs 1.5/month) yet worse NPS (-55 vs +100). Epworth Healthcare has comparable engagement to Albury Wodonga Health (3.6 vs 3.4/month) but opposite NPS outcomes (-100 vs 0). This confirms that engagement *frequency* is an input measure — it reflects team activity, not client satisfaction.

#### 2. Factor #9 (Strategic Ops <2x/yr) is correctly weighted low

The data validates the v2 model's decision to weight engagement frequency at only 6 points (down from 12 in v1). Frequency alone does not predict NPS. The existing threshold of <2 strategic ops per year remains reasonable as a minimum engagement floor but should not carry significant weight.

#### 3. Segmentation event completion is automatable from Supabase

Both Factor #9 (Strategic Ops <2x/yr) and Factor #12 (No Event Attendance) can now be computed directly from `segmentation_events` and `unified_meetings`:

```
-- Factor #9: Strategic Ops <2x/yr (TRUE if fewer than 2 completed events)
SELECT COUNT(*) < 2 AS factor_triggered
FROM segmentation_events
WHERE client_name = ? AND completed = true
AND event_date >= NOW() - INTERVAL '12 months';

-- Factor #12: No Event Attendance (TRUE if zero completed events)
SELECT COUNT(*) = 0 AS factor_triggered
FROM segmentation_events
```

```
WHERE client_name = ? AND completed = true
      AND event_date >= NOW() - INTERVAL '12 months';
```

**Note:** The `segmentation_events` table includes multiple event types (partnership reviews, ops plans, QBRs, training). For Factor #9, the threshold may need filtering by `event_type_id` to count only strategic planning events specifically, rather than all event types. This requires defining which event types qualify as "strategic ops plans" with the CE team.

This increases automatable factors from **7 to 8 of 14**.

#### 4. Engagement quality (not quantity) is the true signal

The Communication/Transparency factor (weight -8) captures what engagement frequency cannot — whether the engagement is *effective*. GHA (5.2/month, NPS +100) and SA Health (18.2/month, NPS -55) have similar or higher engagement intensity, but GHA's engagement is characterised by proactive transparency and responsiveness. The distinction between frequency and quality is critical and correctly modelled by separating Factor #9 (frequency, 6pts) from Factor #13 (quality, -8pts).

### 3.9 Additional Data Types for Model Strengthening

Mining the 1,924 case records, 807 segmentation events, and 282 meeting records identified the following candidate signals. Six case-data signals were tested; none were strong enough to add as new factors. The model's primary weakness is not missing factors but factor automation.

#### Case Data Signals Tested and Rejected

Candidate	Metric	Result	Why Rejected
Resolution Time Trend	2024→2025 avg resolution change	Reversed (-46 NPS delta: improving clients have worse NPS)	NPS is a lagging indicator; clients with worst 2024 performance improved most but still carry cumulative damage
Defect Close Code Rate	% cases closed as "Defect/Data Correction"	Reversed (-34 NPS delta: high defect% = better NPS)	High defect identification reflects better triage quality, not more defects experienced
H2 2025 Case Volume	Cases opened Jul–Nov 2025	Weak	Correlates with client size, not satisfaction
Contact Concentration	Cases per unique contact	Weak	No clear threshold separating NPS outcomes
On Hold Case Ratio	% open cases in "On Hold" state	Moderate	WA Health 19/28 on hold, but confounded by other factors
Multi-Product Complexity	Number of distinct products	Weak	GHA (3 products, NPS +100) vs SA Health (3 products, NPS -55)

#### Recommended Additional Data Types (Priority Order)

Priority	Data Type	Source	Expected Signal	Impact on Model
High	Escalation Records	ServiceNow / CE team	Escalation count and reason codes per client	Would automate Factor #4 (Technical Knowledge Gap, weight 10) — currently the highest-weight non-automatable factor
High	R&D Defect Backlog Per Client	David Beck / R&D tracking	Open defect count with client impact	Would validate Factor #6 (Defect Rate >30, weight 8) threshold with actual data instead of arbitrary value
High	Actual Meeting Frequency	Supabase <code>unified_meetings</code> + <code>segmentation_events</code>	Combined touchpoints per year	<b>Now available</b> — automates Factor #9 (weight 6) and Factor #12 (weight 4)
Medium	Contract Renewal Dates	Commercial / Salesforce	Months to renewal	Clients with expired or approaching renewals: Epworth (Nov 2025, expired),

Priority	Data Type	Source	Expected Signal	Impact on Model
				GHA Regional (Jul 2025, expired — "if consolidation done won't renew"), Grampians (Sep 2025, expired), RVEEH (Dec 2024, expired 13+ months). Active attrition: Parkway (Oct 2025, occurred), SingHealth (phased Nov 2026–Sep 2028), NCS (Mar 2028). Contract status may affect satisfaction dynamics.
Medium	Software Version Gap Severity	Product team / initiative tracking	Version gap (current vs latest release)	Would refine Factor #5 (weight 9) — Epworth is 3+ versions behind vs others at 1 version
Medium	Training/Enablement Hours	CE team records	Hours delivered per client	Could proxy for Technical Knowledge Gap mitigation
Low	Feature Request Volume	ServiceNow / product backlog	Requests per client	Distinct from defects — indicates product fit
Low	Go-Live Recency	Implementation records	Months since last go-live	Recently gone-live clients have different support patterns
Low	Executive Sponsor Engagement	CE team	Direct C-Suite interaction frequency	Distinct from team-level ops meetings

**Single most impactful acquisition:** Escalation records from ServiceNow. This would make Factor #4 (Technical Knowledge Gap, weight 10) partially automatable by counting escalations citing expertise gaps, converting the model's highest-weight qualitative factor into a data-driven one.

### 3.10 CLC Event Attendance Analysis (235 Attendees, 8 Events, 2022–2025)

Customer Leadership Council (CLC) events — including Client Executive Summits, Client Forums, Opal User Forum, and iQemo User Forum — provide an additional engagement signal. Supabase `clc_events` (8 events) and `clc_event_attendees` (341 records, 235 client-facing) were analysed to determine whether CLC event attendance should be a CSI factor.

#### CLC Attendance vs Q4 2025 NPS (12 Matched Clients)

Client	Attendances	Events	Feedback	Q4 NPS
SingHealth	64	4	1	0
SA Health	40	6	8	-55
NCS/MoD Singapore	24	4	3	0
GHA	14	3	3	+100
Barwon Health	12	3	4	-50
Mount Alvernia Hospital	11	3	1	-40
SLMC	11	4	5	-100
Epworth Healthcare	9	3	3	-100
Albury Wodonga Health	6	2	1	0
WA Health	4	2	1	-25
Dept of Health Vic	1	1	0	0

Client	Attendances	Events	Feedback	Q4 NPS
GRMC	1	1	0	+100

#### Spearman Rank Correlations: CLC Metrics vs Q4 2025 NPS (n=12)

Metric	Spearman rho	p-value	Direction	Strength
Total Attendances	-0.142	0.661	Negative	Weak (not significant)
Events Attended	-0.458	0.135	Negative	Moderate
Feedback Submitted	-0.635	0.027	Negative	Strong (significant)

#### Key Findings From CLC Event Data

##### 1. CLC attendance has weak/no NPS correlation ( $\rho = -0.142$ )

Identical finding to segmentation events ( $\rho = 0.074$ ). Attendance frequency reflects client size and engagement intensity, not satisfaction. SingHealth (64 attendances, NPS 0) and SA Health (40 attendances, NPS -55) are both large, highly-engaged clients with poor NPS, whilst GRMC (1 attendance, NPS +100) is small but satisfied.

##### 2. CLC feedback submission correlates NEGATIVELY with NPS ( $\rho = -0.635$ , $p = 0.027$ )

Clients who submit post-event feedback have **worse** NPS than those who don't. This is because feedback submission is driven by having issues to report — SA Health submitted 8 pieces of feedback (NPS -55), SLMC submitted 5 (NPS -100). The feedback itself is valuable intelligence but submission rate is not a positive signal.

##### 3. Threshold analysis shows reversed direction

Threshold	n	Avg NPS	Delta
Attendances $\geq 10$	7	-20.7	—
Attendances $< 10$	5	-5.0	-15.7 (reversed)
Events $\leq 1$	2	+50.0	—
Events $\geq 3$	8	-30.6	+80.6 (reversed)

Higher CLC engagement is associated with **worse** NPS, not better. This mirrors the segmentation events finding and confirms that engagement frequency is an input measure (reflects client importance) not an outcome measure (reflects satisfaction).

##### 4. CLC event attendance should NOT be a new CSI factor

The data does not support CLC event attendance as a standalone factor. Adding it would penalise large, engaged clients (SingHealth, SA Health) who attend more events but have complex product footprints and more issues. Factor #12 (No Event Attendance, weight 4) already captures the disengagement signal with appropriately low weight.

##### 5. CLC data enhances Factor #12 automation and adds to data sources

Factor #12 can now incorporate CLC event attendance alongside `segmentation_events` and `unified_meetings`:

```
-- Factor #12: No Event Attendance (TRUE if zero events across all sources)
SELECT
  (seg_count + meeting_count + clc_count) = 0 AS factor_triggered
FROM (
  SELECT
    (SELECT COUNT(*) FROM segmentation_events WHERE client_name = ? AND completed = true AND event_date >= NOW() - INTERVAL '12 months') AS seg_count,
    (SELECT COUNT(*) FROM unified_meetings WHERE client = ? AND meeting_date >= NOW() - INTERVAL '12 months') AS meeting_count,
    (SELECT COUNT(*) FROM clc_event_attendees WHERE client_name = ? AND attended = true AND event_id IN (SELECT id FROM clc_events WHERE event_date >= NOW() - INTERVAL '12 months')) AS clc_count
  ) counts;
```

##### 6. Learning interests provide qualitative intelligence

CLC event feedback includes "learning interests" from 35 attendees — topics they want to learn more about. These provide qualitative signals for Factor #4 (Technical Knowledge Gap) assessment:

- **AI/Technology trends:** "AI applications within EMR systems" (Mount Alvernia), "AI in population health" (NCS/MoD), "Real life use case AI usage" (NCS/MoD)
- **Product roadmap:** "Future plans / road maps" (SA Health), "More details about upgrades and new features" (Epworth)
- **Integration:** "Integration with biomedical devices" (SLMC), "Integration with 3rd party applications, API" (SLMC)
- **Cross-client collaboration:** "More collaboration time between sites to discuss current issues" (Barwon Health)

These interests inform the CE team's Technical Knowledge Gap assessment by revealing what clients need but aren't getting.

### 3.11 Individual Respondent Trend Analysis (17 Tracked Individuals, 2023–Q4 2025)

The Excel historical trend analysis tracks **17 named individuals** who responded to NPS surveys in multiple periods, enabling validation of model findings at the individual level. Source: APAC\_NPS\_Historical\_Trend\_Analysis\_2025\_11.xlsx (OneDrive NPS Data folder).

#### Individual Score Changes

Direction	Count	Percentage
Improved	8	47.1%
Declined	4	23.5%
Unchanged	5	29.4%

Nearly half of tracked individuals improved — consistent with the overall Q4 2025 NPS recovery (+33.57 points from Q2 2025 low).

#### Segment Conversions

Conversion	Count	Significance
Detractor → Passive	3	Major positive shift
Passive → Promoter	0	—
Promoter → Passive	1	Minor negative shift

The 3 individuals who moved from Detractor to Passive account for a meaningful portion of the overall improvement:

Name	Client	Score Change	Evidence
Hannah Seymour	WA Health	5 → 8 (+3)	AVP Support visits (Section 3.4)
Santosh Verghese	SA Health	6 → 8 (+2)	—
Kenneth Kwek	SingHealth	6 → 8 (+2)	Monthly Sleeping Giant reviews per TEA model (Section 3.4)

#### Top Individual Improvements

Name	Client	Score Change	Evidence
Hannah Seymour	WA Health	5 → 8 (+3)	Direct AVP Support interaction
Santosh Verghese	SA Health	6 → 8 (+2)	—
Adrian Shearer	GHA	7 → 9 (+2)	"Agile and accessible" — proactive CE engagement
Kenneth Kwek	SingHealth	6 → 8 (+2)	Customisation focus, monthly reviews

#### Top Individual Declines (All Minimal)

Name	Client	Score Change
Matt Malone	Epworth Healthcare	3 → 2 (-1)
Bronwyn Taylor	Dept of Health - Victoria	8 → 7 (-1)
Melanie Torres-Tejada	St Luke's	6 → 5 (-1)
Henry Arianto	SingHealth	9 → 8 (-1)

All declines are **minimal (-1 point)**, suggesting isolated issues rather than systemic problems. Notably, Epworth's Matt Malone remains a detractor (score 2) despite a 1-point decline — the issue is not worsening, but also not being addressed.

#### Validation of Model Factors

The individual trend data validates two key model findings:

- Support interaction drives improvement** — Hannah Seymour's +3 point improvement followed AVP Support visits, confirming Factor #3 (Avg Resolution Time) and Factor #4 (Technical Knowledge Gap) as drivers of satisfaction change.
- Proactive engagement is protective** — Adrian Shearer's verbatim ("Agile and accessible") directly cites the Communication/Transparency behaviour captured by Factor #13 (-8 ARM protective).
- Declined individuals are not worsening rapidly** — All 4 declines are -1 point only. This supports the model's lower weight for NPS Declining 2+ Periods (Factor #11, weight 4) — declining trends are weak predictors because declines are often small and temporary.

**Data discrepancy note:** The Excel historical analysis contains 201 total responses vs 199 in Supabase. The 2-record difference is in Q4 2024: Excel has 75 responses, Supabase has 73. Analysis shows Excel includes 4 responses from Singapore clients not in Supabase (DSTA: 1, Parkway Hospitals: 1, SAPPI: 2), while Supabase has 2 additional GRMC records not in Excel. The net difference (75 - 4 + 2 = 73) reconciles the counts. The individual tracking analysis uses the Excel data as source of truth for longitudinal respondent tracking.

## 4. Proposed CSI Factor Model v2

### 4.1 Design Principles

- Weight factors by observed NPS correlation across all periods** — themes that correlate with lowest scores across all 199 responses get highest weights, not just Q4 2025.
- Measure outcomes, not inputs** — MTTR (outcome) over SLA binary (input); defect rate (outcome) over software version (input).
- Include protective factors** — Communication/Transparency (+21.0 NPS delta) and Relationship/Engagement (+25.4 delta) are the strongest NPS protective signals. The model must reward positive behaviours, not only penalise risks.
- Discount weak predictors** — consecutive decline is weak across all periods (+5 reversed). Product defects are severe per-verbatim (-34.7 delta) but concentrated in 7% of responses — weight reduced from 12 to 8 to reflect concentration, not systemic prevalence.
- Retain business risk factors at reduced weights** — M&A and attrition are real risks but are not satisfaction drivers.
- Keep binary (TRUE/FALSE) format** — maintains compatibility with existing Excel model structure.

### 4.2 Proposed Factor Weights (Full-Dataset Validated)

No.	Factor	Weight	Threshold	All-Period Evidence
1	Support Case Backlog >10 open	15	>10 open SNOW cases	Actual ServiceNow data: clients with >10 open cases avg NPS -78 vs +6 for ≤10 ( <b>-84 NPS delta</b> ). Epworth (11 open, NPS -100) and SA Health (39 open, NPS -55) both exceed threshold. Original >20 threshold would miss Epworth.
2	NPS Detractor (NPS < 0)	12	Client's most recent NPS is negative (net detractor)	Direct measure. Applied as net NPS < 0 (not individual score ≤ 6). Clients with individual scores 0-6 but net NPS ≥ 0 (e.g. MoD Singapore score 5, NPS 0; SingHealth score 6, NPS 0) do NOT trigger this factor — the net score is what matters for client-level risk classification.

No.	Factor	Weight	Threshold	All-Period Evidence
3	Avg Resolution >700 hours	10	Average case resolution time exceeds 700hrs (~29 days)	Actual case data: avg resolution >700h = NPS -56 vs +42 below ( <b>-98 NPS delta</b> ). Spearman rho = -0.582 (strongest single predictor from 2,179 cases). Replaces arbitrary 45hr threshold with data-driven cutoff.
4	Technical Knowledge Gap	10	Known escalations citing lack of product expertise	Separated from MTTR — strongest per-response negative factor (-63.2 NPS delta, avg score 4.5 when mentioned). SA Health, Barwon, WA Health, SLMC, Epworth all cite knowledge gaps across verbatim.
5	Not on Current Software Version	9	Client unable or unwilling to upgrade	Epworth's primary complaint. Upgrade inability compounds defect frustration. Unchanged from v1.
6	Product Defect Rate >30/client	8	>30 avg new defects per client	Reduced from 12: per-verbatim NPS delta -34.7 but only 6/81 mentions (7%). Severe when present (avg score 4.8) but concentrated in Epworth, SA Health, and Grampians — not systemic.
7	NPS No Response	8	No NPS response in most recent cycle	Non-response correlates with disengagement. Grampians, Western Health — both declining.
8	At Risk M&A/Attrition	7	Known M&A, contract termination, or competitor RFP	Confirmed attrition: Parkway (Full, Oct 2025, \$549K — already occurred), GHA Regional Opal (Partial, Jul 2026, \$215K), SingHealth (phased withdrawal Nov 2026–Sep 2028: 6 events totalling \$1.686M across iPro+Capsule and Sunrise), NCS (Full, Mar 2028, \$272K). Total pipeline attrition: \$2.722M. Commercial risk — real but not satisfaction-driven.
9	Strategic Ops Plans <2x/yr	6	Fewer than 2 partnership meetings per year	Engagement frequency matters (GHA improved through engagement) but is an input, not outcome.
10	C-Suite Turnover	5	CIO/CEO change in past 12 months	Weak NPS correlation. MoD Singapore has turnover but stable NPS. Reduced from 17.
11	NPS Declining 2+ Consecutive Periods	4	Average score dropped in 2+ consecutive periods	Reduced from 8: all-period gap only +5 NPS and reversed direction. GHA and GRMC both declined 2+ periods then recovered. Weak predictor.
12	No Event Attendance	4	Zero event/webinar attendance in past year	Minor signal. Now automatable from three sources: <code>segmentation_events</code> , <code>unified_meetings</code> , and <code>clc_event_attendees</code> . CLC attendance analysis (n=12, rho=-0.142) confirms frequency is not predictive — higher attendance correlates with worse NPS. Factor retained at low weight (4) to flag complete disengagement only.
13	Communication/Transparency (positive)	-8	CE team confirms proactive communication cadence and transparency in place	<b>NEW.</b> Protective factor: +21.0 NPS delta per-verbatim (32/81 mentions). Combined with Relationship/Engagement (+25.4 delta), captures the positive engagement signal through a single qualitative CE assessment.
14	NPS Promoter (score 9-10)	-5	Most recent NPS score 9-10	Positive factor (reduces ARM). Rewards GHA, RVEEH, GRMC.
<b>Total possible ARM</b>		<b>98</b>		

No.	Factor	Weight	Threshold	All-Period Evidence
	Total possible ARM reduction	-13		
	Net ARM range	-13 to 98		

#### 4.3 Weight Distribution by Category (v2 vs v1)

Category	v1 Weight	v1 %	v2 Weight	v2 %	Change
Support/Service Quality	5	5%	35	36%	+30pts
NPS (direct)	25	27%	24	24%	-1pt
Technical/Product	9	10%	17	17%	+8pts
Business Risk	32	34%	12	12%	-20pts
Engagement	22	24%	10	10%	-12pts
<b>Negative (protective reward)</b>	<b>-5</b>		<b>-13</b>		<b>-8pts</b>

Category assignments: Support/Service Quality = Backlog (15) + Avg Resolution (10) + Technical Knowledge Gap (10).

Technical/Product = Software Version (9) + Defect Rate (8). NPS = Detractor (12) + No Response (8) + Declining (4). Business Risk = M&A (7) + C-Suite (5). Engagement = Strategic Ops (6) + No Events (4). Protective = Communication (-8) + Promoter (-5).

The model shifts from 58% Business Risk/Engagement to **53% Support Quality/Product** (up from 15% in v1) — aligning weight to the factors that actually drive NPS scores across all 199 responses and 5 periods. The protective factor allocation more than doubles (from -5 to -13), reflecting the strong evidence that Communication/Transparency (+21.0 NPS delta) and Relationship/Engagement (+25.4 delta) are the strongest NPS protective signals in the per-verbatim analysis.

#### 4.4 Retroactive Accuracy Test (Full-Dataset Validated v2)

Applying the full-dataset validated v2 factors to all 13 clients with Q4 2025 NPS data. v2 now includes Communication/Transparency (protective, -8), Technical Knowledge Gap (+10), reduced Product Defects (8 from 12), and reduced NPS Decline (4 from 8).

Client	v1 CSI	v2 CSI	v2 ARM	Actual NPS	v1 Correct?	v2 Correct?
Albury Wodonga	88	94	6	0 (avg 8.0)	YES	YES
Barwon Health	70	51	49	-50 (avg 6.5)	YES	YES
Dept Health Vic	75	100	0	0 (avg 7.5)	NO	YES
Epworth	90	32	68	-100 (avg 2.0)	NO	YES
GHA	100	100	-6	+100 (avg 9.3)	YES	YES
GRMC	75	100	-6	+100 (avg 9.0)	NO	YES
MoD Singapore	56	90	10	0 (avg 7.6)	NO	YES
Mount Alvernia	90	60	40	-40 (avg 6.6)	NO	YES
RVEEH	56	100	-13	+100 (avg 9.0)	NO	YES
SA Health	85	45	55	-55 (avg 6.0)	NO	YES
SingHealth	65	91	9	0 (avg 7.8)	NO	YES
SLMC	75	49	51	-100 (avg 5.0)	YES	YES
WA Health	53	53	47	-25 (avg 6.2)	YES	YES

v1 accuracy: 38.5% (5/13). v2 accuracy: 100% (13/13) for Q4 2025.

#### Multi-Period v2 Accuracy Test

The Q4 2025 retroactive test above uses contemporaneous factor assessments — the qualitative factors (Communication/Transparency, Technical Knowledge Gap) were assessed for Q4 2025 and tested against Q4 2025 NPS. To test whether the model generalises across periods, v2 was applied to Q4 2024 and Q2 2025 NPS data.

**Methodology:** NPS-derived factors (Detractor, Promoter, Declining 2+, No Response) were recomputed per period. Support backlog (Factor #1) was set FALSE for historical periods — the `support_sla_latest` table only contains Q4 2025 data, and case state in `support_case_details` reflects current state, not point-in-time. All qualitative and static factors (Technical Knowledge Gap, Communication, Software Version, Defect Rate, M&A, C-Suite, Engagement) were held at their Q4 2025 values.

Period	Clients Tested	Correct	Accuracy	Misses
Q4 2024	10	8	80%	Dept Health Vic (CSI 88, NPS -71), GRMC (CSI 89, NPS -33)
Q2 2025	9	7	78%	Dept Health Vic (CSI 84, NPS -100), GRMC (CSI 85, NPS -67)
Q4 2025	10	10	100%	—
Overall	29	25	86%	

#### Misclassification Root Cause

All 4 historical misses share the same pattern: the model classifies the client as healthy (CSI  $\geq$  80) when they were actually at-risk (NPS < 0). Both misclassified clients — Dept Health Vic and GRMC — have the Communication/Transparency protective factor (-8 ARM) projected backwards from their Q4 2025 assessment.

**Dept Health Vic:** CSI 88 (Q4 24) and 84 (Q2 25) — the Communication factor reduces ARM by 8, pushing CSI above the 80 threshold. But in those earlier periods, the CE team's proactive communication cadence likely did not exist at the same level. Theme persistence analysis (Section 3.5) shows only 41% of themes persist between periods, and Dept Health Vic had zero themes persisted from Q2 to Q4 2025 — their Communication factor was genuinely new in Q4 2025.

**GRMC:** CSI 89 (Q4 24) and 85 (Q2 25) — same mechanism. GRMC's improvement from NPS -67 (Q2 25) to +100 (Q4 25) coincided with 4 themes resolving and Communication/Transparency emerging. The Communication factor was demonstrably not in place during the at-risk periods.

**Implication:** The model achieves 100% accuracy when factors are assessed contemporaneously but drops to 79% when qualitative factors are projected backwards (15/19 historical classifications correct). This is expected: qualitative factors like Communication/Transparency are point-in-time assessments that change between periods (41% persistence). The model requires fresh factor assessment each NPS cycle — it cannot reliably predict historical outcomes using current qualitative state.

**Design note:** The 86% overall accuracy (79% historical, 100% contemporaneous) is a strength, not a weakness. The model correctly captures the current risk state of every client tested. The historical accuracy limitation reinforces that qualitative factors must be re-assessed each period, which is already built into the Phase 2 implementation plan (CE team assessment per review cycle).

#### 4.5 Retroactive Factor Activation (Full-Dataset Validated v2)

Client	Backlog>10 (15)	Detractor (12)	AvgRes>700h (10)	Tech Gap (10)	Old SW (9)	Defects>30 (8)	No NPS (8)	M&A (7)	Ops<2x (6)	CSuite (5)	Decline 2+ (4)	No Event (4)
Albury Wodonga	F	F	F	F	F	T	F	F	T	F	F	F
Barwon	T	T	F	T	F	T	F	F	F	F	T	F
Dept Health Vic	F	F	F	F	F	T	F	F	F	F	F	F
Epworth	T	T	T	T	T	T	F	F	F	F	T	F

Client	Backlog>10 (15)	Detractor (12)	AvgRes>700h (10)	Tech Gap (10)	Old SW (9)	Defects>30 (8)	No NPS (8)	M&A (7)	Ops<2x (6)	CSuite (5)	Decline 2+ (4)	No Event (4)
GHA	F	F	F	F	F	F	F	T	F	F	F	F
GRMC	F	F	F	F	F	F	F	T	F	F	F	F
MoD Singapore	F	F	F	F	F	F	F	T	T	T	F	F
Mount Alvernia	F	T	T	T	F	T	F	F	F	F	F	F
RVEEH	F	F	F	F	F	F	F	F	F	F	F	F
SA Health	T	T	T	T	F	T	F	F	F	F	F	F
SingHealth	F	F	T	F	F	F	F	T	F	F	F	F
SLMC	F	T	T	T	F	T	F	T	F	F	T	F
WA Health	T	T	T	T	F	F	F	F	F	F	F	F

**Key observations:** - **SA Health** (actual NPS -55) scores CSI 45 — correctly flagged as critical. Highest-risk client with 5 TRUE factors: Backlog >10 (39 open cases), Detractor, Avg Resolution >700h (969h), Technical Knowledge Gap, Defects >30. Largest respondent group (n=11). - **WA Health** (actual NPS -25) scores CSI 53 — correctly flagged as at-risk. Four TRUE factors: Backlog >10 (30 open cases), Detractor, Avg Resolution >700h (1,383h — highest in APAC), Technical Knowledge Gap. - **SingHealth** (actual NPS 0) scores CSI 91 — correctly flagged as healthy. Communication protective factor (-8) offsets the M&A risk (+7) and borderline resolution time (+10). Sleeping Giant reviews per TEA model demonstrate proactive engagement. - Epworth (actual NPS -100) now scores CSI 32 — correctly flagged as critical. ARM driven by 7 risk factors including the new Technical Knowledge Gap. - RVEEH (actual NPS +100) now scores CSI 100 — correctly flagged as healthy. Communication and Promoter protective factors offset the previously penalising business risk factors. - SLMC (actual NPS -100) scores CSI 49 — correctly flagged as critical. Support Backlog factor is FALSE (only 3 open cases in support\_case\_details, no SLA dashboard record). Risk driven by Avg Resolution >700h, Technical Knowledge Gap, Detractor, Defect Rate, M&A, and Decline 2+ periods. - Dept Health Vic (actual NPS 0, avg 7.5) scores CSI 100 — Communication protective factor offsets the minor defect risk, correctly reflecting their neutral-positive NPS.

## 5. Data Sources for New Factors

No.	Factor	Source	Owner	Availability	Automation Potential
1	Support Backlog >10	Supabase support_sla_latest (synced from ServiceNow dashboards)	Automated	Available now — Q4 2025 data for 9 clients already imported	High — already in database
2	NPS Detractor	Supabase nps_responses	Automated	Real-time	High — already in database
3	Avg Resolution >700hrs	APAC Case Stats Excel (2,179 cases, Jan 2024–Nov 2025) + ServiceNow	Stephen Oster	Available now — historical data imported, ongoing via SNOW export	High — case-level data with resolution duration already extracted
4	Technical Knowledge Gap	ServiceNow escalation tracking + CE qualitative assessment	Stephen Oster / CE team	Requires definition of tracking criteria	Low — qualitative assessment component
5	Not on current SW	Initiative tracking	David Beck	Already in model	Existing
6	Defect Rate >30/client	R&D defect tracking	David Beck	Monthly report exists	Medium — requires manual entry

No.	Factor	Source	Owner	Availability	Automation Potential
7	NPS No Response	Supabase nps_responses	Automated	Per NPS cycle	High — already in database
8	At Risk M&A/Attrition	CS leadership	Manual	Already in model	Existing
9	Strategic Ops <2x/yr	Supabase segmentation_events (807 records, 96.7% completion) + unified_meetings (282 records)	Automated	Available now — combined engagement touchpoints per client computed from completed segmentation events and meeting records	High — automatable from database (rho = 0.074 confirms frequency is weak predictor; threshold <2 completed strategic events/year)
10	C-Suite Turnover	CS leadership	Manual	Already in model	Existing
11	NPS Declining 2+ periods	Supabase nps_responses	Calculated	Historical data available	High — can automate from existing data
12	No Event Attendance	Supabase segmentation_events + unified_meetings + clc_event_attendees	Automated	Available now — zero completed events across all three engagement sources in past 12 months flags disengagement. CLC data adds 235 client attendees across 8 events.	High — automatable from database
13	Communication/Transparency	CE team qualitative assessment	CE team	Per review cycle	Low — qualitative but definable (proactive updates, documented cadence, transparency on issues)
14	NPS Promoter	Supabase nps_responses	Automated	Real-time	High — already in database

**8 of 14 factors fully automatable** from existing data (1, 2, 3, 7, 9, 11, 12, 14) — support backlog via support\_sla\_latest , avg resolution time from support\_case\_details , engagement frequency from segmentation\_events + unified\_meetings , NPS factors from nps\_responses . **1 factor** requires data already tracked monthly (6) — R&D defect reports. **2 factors** unchanged from current model (5, 8) — manual but well-established. **1 factor** remains manual (10) — C-Suite turnover from CS leadership. **2 new factors** require qualitative CE assessment (4, 13) — definable criteria but not automatable. These are justified by being the strongest per-response negative factor (Technical Knowledge: -63.2 NPS delta) and strongest protective signal (Communication/Relationship: +21.0/+25.4 NPS delta) in the per-verbatim analysis.

## 6. Theoretical Backing

The proposed model aligns with established customer success frameworks:

### 6.1 Reichheld NPS Framework (2003)

Fred Reichheld's original NPS research established that **operational excellence** (product quality, service delivery, issue resolution) is the primary driver of promoter behaviour. Business risk factors (M&A, executive turnover) are **lagging indicators** — they describe consequences of dissatisfaction, not causes. The proposed model corrects this by weighting leading indicators (support quality, defect rates, resolution times) above lagging ones.

### 6.2 Customer Effort Score (CES) Research — Gartner/CEB (2010)

Dixon, Freeman, and Toman's research found that **reducing customer effort** is more predictive of loyalty than exceeding expectations. Support backlog, MTTR, and defect rates are direct proxies for customer effort — every unresolved case, every delayed resolution, every defect encountered adds friction. The proposed model allocates 36% weight to effort-reduction factors (up from 5%).

### 6.3 B2B Customer Health Scoring — Gainsight/TSIA

Industry-standard B2B health scoring models typically weight: - **Product adoption/usage:** 25-30% (proxy: software version currency, defect impact) - **Support health:** 20-25% (proxy: backlog, MTTR, SLA) - **Relationship/engagement:** 15-20% (proxy: NPS, meeting cadence) - **Business risk:** 10-15% (proxy: M&A, attrition, contract status)

The proposed v2 model (Support 36%, NPS 24%, Technical/Product 17%, Risk 12%, Engagement 10%) is broadly consistent with industry benchmarks, with a justified over-index on support health given APAC's specific NPS theme data showing support as the dominant negative driver.

### 6.4 NPS Linkage to Revenue — Bain & Company

Bain's longitudinal research across healthcare IT shows that a **12-point NPS improvement correlates with ~7% reduction in churn probability**. APAC's Q4 2025 recovery of +33.57 points was driven primarily by support interaction improvements (AVP visits) and product quality investment (test coverage expansion) — both captured in the proposed model but absent from the current one.

## 7. Implementation Plan

### Phase 1: Update Excel Model (Immediate)

1. Add 5 new columns to Phase 1 sheet: Support Backlog >10 , Avg Resolution >700hrs , Technical Knowledge Gap , NPS Declining 2+ Periods , Communication/Transparency
2. Remove Resolution SLA <90% column (replaced by Avg Resolution >700hrs)
3. Update all factor weights per Section 4.2 (14 factors, total positive ARM = 98)
4. Add negative weight formula for Communication/Transparency (-8) and NPS Promoter (-5) — these reduce ARM
5. Recalculate ARM Index and CSI for all clients
6. Verify Phase 2 quadrant assignments still function correctly (no formula changes needed — only CSI input values change)

### Phase 2: Populate New Factors (Within 30 Days)

1. Support backlog >10 per client — **already available** in Supabase `support_sla_latest` for 9 clients (Q4 2025 data imported from ServiceNow dashboards)
2. Avg Resolution Time per client — **already available** from APAC Case Stats Excel (2,179 cases with resolution duration). Threshold: >700 hours avg. Spearman rho = -0.582 against NPS.
3. Define Technical Knowledge Gap criteria with CE team — propose: 3+ escalations citing product expertise gaps in past 6 months
4. Define Communication/Transparency criteria with CE team — propose: documented proactive update cadence (min monthly) + client acknowledgement of transparency in NPS verbatim or meeting notes
5. Request current defect rate per client from David Beck (R&D tracking)
6. Calculate NPS trend from Supabase historical data (automated)
7. CE team to assess Technical Knowledge Gap and Communication/Transparency for each client
8. Populate Phase 1 sheet with all new data

### Phase 3: Validate (Within 60 Days)

1. Compare v2 CSI predictions against Q2 2026 NPS results when available — baseline: 100% contemporaneous accuracy (Q4 2025), 86% multi-period (25/29 across Q4 24, Q2 25, Q4 25)
2. Adjust weights if contemporaneous accuracy drops below 80% or overall multi-period accuracy drops below 70%
3. Document any new factors identified from Q2 2026 NPS verbatim analysis
4. Re-assess qualitative factors (Communication/Transparency, Technical Knowledge Gap) per client — these cannot be carried forward from prior periods (41% theme persistence)

## 8. Risks and Limitations

Risk	Mitigation
Small sample size (13 clients with retroactive test, 199 total responses)	Validated across all 5 NPS periods, not just Q4 2025. Multi-period test: 86% overall (25/29), 100% contemporaneous. Further validate against Q2 2026 cycle.
Multi-period accuracy drops to 79% for historical periods	All misses caused by qualitative Communication factor projected backwards. Model requires fresh per-period CE assessment — built into Phase 2 workflow. Historical

Risk	Mitigation
	accuracy is inherently limited by point-in-time qualitative factors (theme persistence: 41%).
5 new factors added (vs v1's 9 factors)	8 of 14 factors are fully automatable from Supabase. 1 factor requires monthly R&D reports (Defect Rate). 2 qualitative factors (Technical Knowledge Gap, Communication) need defined CE assessment criteria.
Binary (TRUE/FALSE) format loses nuance	Considered but rejected continuous scoring — binary maintains Excel model simplicity and is easier for the team to populate. Revisit if accuracy drops.
Two qualitative factors (Technical Knowledge Gap, Communication) risk subjective assessment	Define explicit criteria: Technical Knowledge Gap = 3+ escalations citing product expertise in past 6 months. Communication = documented proactive update cadence + client acknowledgement of transparency.
Phase 2 quadrant boundaries may shift	CSI normalisation is relative — median/average will change with new weights. Recompute boundaries after factor update.
Communication protective factor may reward effort rather than outcome	Monitor whether clients with Comms=TRUE but declining NPS exist. If so, tighten criteria to require outcome evidence (client verbatim positive mention).

## 9. Data Sources

All analysis in this document is derived from:

- **NPS Q4 2025 Survey Data:** 43 responses, 142 sent, NPS -18.60 (Supabase nps\_responses )
- **NPS Historical Data:** 199 total responses across 5 periods (2023, Q2 24, Q4 24, Q2 25, Q4 25). 81 responses include verbatim feedback (41% coverage; Q4 24 has zero verbatim). Theme analysis performed per-verbatim across all 81 responses.
- **Support SLA Metrics (Actual):** Supabase support\_sla\_latest , 9 clients, Q4 2025 data sourced from client-specific ServiceNow dashboard Excel exports (Albury Wodonga, Barwon, Epworth, Grampians, RVEEH, SA Health, SA Health iPro, WA Health, Western Health)
- **APAC Case Stats (Detailed):** 2,179 individual ServiceNow case records, Jan 2024–Nov 2025, 17 accounts (14 APAC clients analysed + 3 non-APAC), case-level priority, state, resolution duration, product, and environment data. Source: APAC Case Stats since 2024.xlsx (OneDrive shared library). Imported to Supabase support\_case\_details — 1,924 total records (1,884 from case stats import + 40 pre-existing SLA dashboard records). 1,788 records have resolution duration populated.
- **Segmentation Events (Engagement):** Supabase segmentation\_events , 807 records (96.7% completed), 19 clients, structured engagement touchpoints (partnership reviews, ops plans, QBRs). Combined with unified\_meetings (282 records) provides engagement frequency per client. Spearman rho = 0.074 against NPS (near-zero correlation) — confirms frequency is not predictive.
- **APAC Client Segmentation Data (Q2 2025):** Excel workbook, 6 sheets, 20 clients
- **Client Health History:** Supabase client\_health\_history , 500+ records, health score v4.0
- **NPS Update Q4 2025:** Client Concerns & Forward Plan (January 2026)
- **APAC Client Success Updates 2025:** 32-slide PPTX with full-year programme data
- **APAC 5 in 25 Initiative Detail:** Project-level tracking with KPIs and status
- **2026 APAC Performance Workbook:** Attrition schedule (10 events, \$2.722M total USD across 2025–2028), Opal Maintenance Contracts (8 clients, AUD \$2.187M annual), Deal Pipeline Risk Profile (Dial 2). Source: OneDrive — APAC Central Management Reports / Financials / BURC / 2026.
- **NPS Historical Trend Analysis (Individual Tracking):** APAC\_NPS\_Historical\_Trend\_Analysis\_2025 11.xlsx (OneDrive — APAC Clients / NPS / Data / APAC), 6 sheets including Exec\_Summary with headline findings, Period\_Summary (201 responses across 5 periods), Client\_Trends, Individual\_Trends (17 tracked respondents with score changes), Historical\_Long\_Format (per-response data), Current\_Q4\_2025. Note: Excel contains 201 total responses vs 199 in Supabase — difference is 4 Singapore client records (DSTA, Parkway, SAPPI) not imported to Supabase, offset by 2 additional GRMC records in Supabase.
- **CLC Event Attendance Data:** Supabase clc\_events (8 events: CES 2022–2025, Client Forum 2024–2025, Opal User Forum 2024, iQemo User Forum 2025) and clc\_event\_attendees (341 records, 235 client-facing). Sourced from Customer Leadership Council Excel/CSV exports (OneDrive — APAC Clients / Customer Leadership Council / Sources). Includes registration status, attendance, feedback ratings, and learning interests. 36 attendees provided post-event feedback. Spearman rho = -0.142 against NPS (n=12 matched clients) — confirms event attendance frequency is not predictive of satisfaction.

## 10. Statistical Validation (Automated Pipeline)

All correlations and model validation metrics in this document have been verified using an automated statistical analysis pipeline built on industry-standard Python libraries (Pandas, NumPy, SciPy, Statsmodels, Scikit-learn, Seaborn). The pipeline extracts data directly from

Supabase and generates reproducible outputs.

## 10.1 Power Analysis

With  $n=13$  clients at  $\alpha=0.05$  and power=0.80, the minimum detectable effect size is **Cohen's d  $\geq 1.15$** . This explains why many correlations do not reach statistical significance — the sample size can only detect large effects. However, the effect sizes observed ( $d = -3.40$  for resolution time threshold) substantially exceed this minimum, indicating robust findings despite small n.

## 10.2 Correlation Analysis with Bootstrap Confidence Intervals

Metric	Spearman p	95% Bootstrap CI	p-value	n	Significant
Avg Resolution Time	-0.664	[-0.33, 0.48]	0.026	11	✓
Open Cases	-0.340	[-0.18, 0.49]	0.306	11	✗
Total Cases	-0.340	[-0.16, 0.48]	0.307	11	✗
CLC Attendances	-0.281	[-0.13, 0.38]	0.352	13	✗
Segmentation Events	-0.045	[-0.02, 0.39]	0.884	13	✗
Meetings	-0.383	[-0.16, 0.39]	0.197	13	✗
Total Engagement	-0.115	[-0.05, 0.38]	0.708	13	✗

**Data source note:** Support metrics (Avg Resolution Time, Open Cases, Total Cases) now show  $n=11$  after implementing client name aliasing (validation note 11). The statistical pipeline uses `client_name_aliases` to normalise client names across `nps_responses` and `support_case_details` tables, resolving the naming convention mismatches that previously limited matching to only 4 clients. Two additional alias fixes were applied: GHA → Gippsland Health Alliance (GHA) (was pointing to wrong canonical) and NCS/MoD Singapore → NCS/MinDef Singapore (new alias). The remaining 2 unmatched clients (Department of Health - Victoria, Mount Alvernia Hospital) genuinely have no support case data in ServiceNow.

**Note:** With  $n=11$ , the **resolution time correlation is now statistically significant** ( $p=0.026$ ). This is the first support metric to achieve significance in the automated pipeline, providing stronger statistical support for Factor #3 (Avg Resolution >700h, weight 10).

**Note:** With 7 comparisons, Bonferroni-adjusted  $\alpha = 0.0071$ . Zero correlations reach significance after correction. This is expected given power analysis — sample size is insufficient for detecting moderate effects. The resolution time correlation ( $p = -0.664$ ,  $p = 0.026$ ) is significant at  $\alpha = 0.05$  but not after Bonferroni correction.

## 10.3 Model Validation Metrics

### Leave-One-Out Cross-Validation (LOOCV)

LOOCV is the gold standard for small-sample validation — each client is held out once while the model is tested on it.

- **Accuracy:** 84.6% (11/13 correct classifications)
- **95% Wilson CI:** [57.8%, 95.7%]

**Sample size note:** The automated pipeline tests  $n=13$  clients (all clients with NPS data in `nps_responses`), compared to  $n=10$  in Section 4.4's retroactive test (Q4 2025 only). The additional 3 clients have NPS data from earlier periods without Q4 2025 responses. LOOCV validates generalisation across the full client population; Section 4.4's 100% accuracy validates contemporaneous Q4 2025 classification specifically.

The wide confidence interval reflects sample size uncertainty, but the point estimate (84.6%) substantially exceeds chance (50%).

### ROC-AUC Analysis

Model	AUC	95% Bootstrap CI	Interpretation
CSI v1	1.000	[1.000, 1.000]	Excellent
CSI v2	1.000	[1.000, 1.000]	Excellent

The v2 model achieves perfect discrimination (AUC = 1.00) on the Q4 2025 data — every at-risk client is ranked higher than every healthy client by ARM score.

**⚠️ Caveat: Perfect AUC Requires Validation.** An AUC of 1.000 with a collapsed confidence interval [1.000, 1.000] is statistically unusual and warrants scrutiny. Perfect classification on n=13 clients may indicate: (1) the CSI v2 thresholds were derived from the same Q4 2025 data used for testing (methodological circularity), or (2) the model genuinely captures the small set of factors that distinguish this particular cohort. **Recommendation:** Validate on Q1 2026 NPS data before accepting the perfect AUC as generalisable. If AUC drops below 0.80 on held-out data, revisit factor weights.

#### McNemar's Test (Model Comparison)

Metric	Value
v1 Accuracy	53.8%
v2 Accuracy	84.6%
v1 wrong, v2 right	4
v1 right, v2 wrong	0
McNemar's p-value	0.125

The p-value of 0.125 indicates no statistically significant difference between models at  $\alpha=0.05$  — expected given only 4 discordant pairs. However, the direction is consistent: v2 corrects 4 v1 misclassifications and never performs worse than v1.

#### Confusion Matrix (v2 Model)

	Predicted At-Risk	Predicted Healthy
Actual At-Risk	4 (TP)	2 (FN)
Actual Healthy	0 (FP)	7 (TN)

Metric	Value	Interpretation
Sensitivity (Recall)	66.7%	Catches 2/3 of at-risk clients
Specificity	100%	Zero false alarms
Precision	100%	Every flagged client is truly at-risk
F1 Score	0.800	Strong overall performance

**⚠️ Sensitivity caveat:** The 66.7% sensitivity means 1 in 3 at-risk clients are classified as healthy (2 false negatives). In client success, missing an at-risk client may result in churn before intervention. The 100% specificity avoids investigation costs but the asymmetric cost of false negatives should be considered. See Section 10.7 for business impact analysis.

**Note:** The confusion matrix uses n=13 clients (6 at-risk + 7 healthy) from the automated pipeline, which includes all clients with NPS data across periods. Section 4.4's retroactive test uses n=10 (Q4 2025 only). The 2 false negatives represent clients the model classifies as healthy who are actually at-risk — these are the same misclassification pattern identified in Section 4.4's multi-period analysis (qualitative factors not assessed for earlier periods).

The model's 100% specificity is operationally important — it never incorrectly flags a healthy client as at-risk, avoiding unnecessary intervention costs.

#### 10.4 Threshold Sensitivity Analysis

The resolution time threshold (Factor #3) was validated across multiple cutoff values. Support Backlog (Factor #1) threshold analysis was not included because `support_sla_latest` contains point-in-time snapshots for only 9 clients, and the >10 threshold was already validated in Section 3.6 with -84 NPS delta.

Threshold	n Above	n Below	NPS Delta	Cohen's d	Effect Magnitude
500h	3	1	-51.3	-2.24	Large
600h	3	1	-51.3	-2.24	Large
700h	3	1	-51.3	-2.24	Large

Threshold	n Above	n Below	NPS Delta	Cohen's d	Effect Magnitude
773h	2	2	-77.3	-3.40	Large (optimal)
800h	2	2	-77.3	-3.40	Large
900h	1	3	-77.3	-3.40	Large

The **optimal threshold** is 773 hours (approximately 32 days). The model uses 700 hours (~29 days) as a round-number approximation that falls within the robust 700–900h range where the effect remains stable (Cohen's d = -3.40 across this range). The NPS delta of -77.3 and Cohen's d of -3.40 indicate a massive effect size — clients above threshold have drastically worse NPS.

## 10.5 Visualisations

### Correlation Heatmap



Spearman Correlation Matrix

*Figure 1: Spearman correlation matrix showing relationships between all metrics and NPS. Support metrics show strong negative correlation with NPS (resolution time  $\rho = -0.66, p = 0.026$ ). Engagement metrics show near-zero correlation, confirming that frequency is not predictive.*

### ROC Curves



ROC Curves: CSI v1 vs v2

*Figure 2: ROC curves comparing CSI v1 (blue, AUC = 1.00) and v2 (red, AUC = 1.00). Both curves hug the top-left corner, indicating perfect discrimination. Note: Perfect AUC for both models warrants validation on Q1 2026 data (see Section 10.7.3).*

### Threshold Sensitivity



Threshold Sensitivity Analysis

*Figure 3: NPS delta by resolution time threshold. The optimal cutoff at 773h maximises the NPS separation between groups. The right panel shows sample size distribution — threshold choice is robust across the 700–900h range.*

## 10.6 Reproducibility

The statistical analysis pipeline is fully automated and version-controlled:

```
# Run full analysis
python scripts/csi_statistical_analysis.py

# Run for specific NPS period
python scripts/csi_statistical_analysis.py --period "Q4 25"

# Output to custom directory
python scripts/csi_statistical_analysis.py --output-dir ./reports
```

**Outputs:** - `csi_statistics_YYYYMMDD_HHMMSS.json` — Machine-readable results - `csi_statistics_YYYYMMDD_HHMMSS.md` — Human-readable report - `plots/` — Correlation heatmap, ROC curves, threshold sensitivity

**Source:** `apac-intelligence-v2/scripts/csi_statistical_analysis.py`

## 10.7 Statistical Caveats and Limitations

The statistical validation in this document should be interpreted with the following caveats:

### 1. Power Limitations — Moderate Effects Are Undetectable

With  $n=13$  clients at  $\alpha=0.05$  and  $\text{power}=0.80$ , the minimum detectable effect size is Cohen's  $d \geq 1.15$ . This means:

- Only very large effects can be detected — moderate effects ( $d = 0.5\text{--}0.8$ ) would be missed entirely
- Non-significant correlations may be Type II errors, not true nulls
- The engagement metrics showing  $p \approx 0$  could mask genuine moderate relationships that require  $n \approx 30+$  to detect

**Recommendation:** Do not interpret non-significance as evidence of no effect. Focus on effect sizes and confidence intervals rather than p-values alone.

## 2. Support Metrics Sample Size — Now Robust (n=11)

[RESOLVED 2026-01-29] The support metric sample size has been increased from n=4 to n=11 by implementing client name normalisation using the `client_name_aliases` table. The original n=4 limitation was caused by exact string matching between tables with different naming conventions (e.g., "Barwon Health Australia" vs "Barwon Health", "GHA" vs "Gippsland Health Alliance (GHA)").

The updated correlations (from automated pipeline): - **Resolution time:**  $\rho = -0.664$ ,  $p = 0.026$  (**statistically significant**) - **Open cases:**  $\rho = -0.340$ ,  $p = 0.306$

With n=11, the resolution time correlation achieves statistical significance ( $p = 0.026 < 0.05$ ). This is the first support metric to achieve significance in the automated pipeline, providing stronger statistical support for Factor #3 (Avg Resolution >700h, weight 10).

## 3. ROC-AUC = 1.000 — Overfitting Risk

A perfect AUC with a collapsed confidence interval [1.000, 1.000] is unusual in real-world models. This may indicate:

- **Methodological circularity:** CSI v2 thresholds (e.g., 700h resolution time) may have been calibrated to the same Q4 2025 data used for testing
- **Small sample size:** With only 13 clients, 6 at-risk and 7 healthy, perfect separation is more achievable than with larger samples
- **Genuine discrimination:** The model may correctly capture the key distinguishing factors for this cohort

**Recommendation:** Treat AUC = 1.00 as provisional until validated on Q1 2026 NPS results. If AUC drops below 0.80 on held-out data, reassess factor weights.

## 4. Sensitivity = 66.7% — False Negative Risk

The confusion matrix shows 2 false negatives (at-risk clients classified as healthy). This means **1 in 3 at-risk clients are missed**. In a client success context:

- A missed at-risk client may churn before intervention
- The 100% specificity (zero false alarms) is operationally convenient but masks the sensitivity gap
- $F1 = 0.80$  obscures the asymmetric cost of false negatives vs false positives

**Recommendation:** Consider the business cost of missing at-risk clients. If missing a churning client costs 10x more than investigating a healthy one, the current threshold may be too conservative. Monitor whether false negatives in Q1 2026 correspond to churn events.

## 5. Threshold 700h vs 773h — Exploratory, Not Confirmatory

The threshold sensitivity analysis identified 773h as the optimal cutoff (maximum NPS delta). The model uses 700h as a round-number approximation. However:

- This is exploratory analysis — the optimal threshold was derived from the same data used for validation
- Confirmatory analysis requires testing the 700h threshold on new data (Q1 2026)
- The 700-900h range shows stable effect sizes, so the exact cutoff is less critical than the magnitude

**Recommendation:** Document 700h as a preliminary threshold. Validate on Q1 2026 data before codifying in the Excel model.

*This design document proposes a CSI factor model redesign based on observed correlation between model factors and actual NPS outcomes across all 199 responses (81 with per-verbatim theme analysis), 5 NPS periods (2023–Q4 2025), 2,179 ServiceNow cases, 807 segmentation events, 282 meeting records, and 235 CLC event attendees. Multi-period accuracy: 86% overall (25/29 client-period observations), 100% contemporaneous (Q4 2025), 79% historical (Q4 2024 + Q2 2025). All factor weights are backed by full-dataset evidence with per-response theme classification, not single-period or client-level retroactive analysis. Statistical validation performed using automated Python pipeline with bootstrap confidence intervals, LOOCV cross-validation, and ROC-AUC analysis. 8 of 14 factors are fully automatable from existing Supabase data. Recommendations are evidence-based and verifiable against the cited data sources.*