

StARS Hospital Simulation Suite

Methods, math, and reproducible outputs for internal validation using publicly available hospital operations datasets (Australia, England, New Zealand).

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Executive summary

This report documents three hospital-focused simulation datasets and a sensitivity analysis suite used to demonstrate StARS scoring behavior under the Mena Dominance Law. The simulations are based exclusively on public, non-patient operational data (counts, rates, capacity). Each dataset is transformed into two competing channels—Agent Stress Load (ASL) and Code Vulnerability (CV)—then evaluated via the dominance differential $\Delta = \text{ASL} - \text{CV}$ to generate a correction mandate (Agent Stabilization, Structural Correction, or Dual-Path). A rule-based intervention simulation applies targeted reductions to the dominant channel to illustrate expected directional impact.

Outputs included with the simulation folder

Dataset	Primary output CSV	Sensitivity output CSV
Australia (AIHW ED + resources)	stars_internal_simulation_australia_state_year.csv	stars_hospital_sensitivity_australia_state_year.csv
England (NHS KH03 beds)	stars_internal_simulation_uk_beds_region_quarter.csv	stars_hospital_sensitivity_uk_beds_region_quarter.csv
New Zealand (publicly funded discharges)	stars_internal_simulation_nz_dhb_2018_2019.csv	stars_hospital_sensitivity_nz_dhb_2018_2019.csv

Core model (common across all simulations)

StARS decomposes misalignment into two channels:

ASL: operational load carried by the agent layer (work intensity, saturation, throughput pressure). **CV:** structural vulnerability of the governing architecture (capacity bottlenecks, complexity, imbalance, leakage).

The Mena Dominance Law defines the dominance differential:

$$\Delta = \text{ASL} - \text{CV}$$

A dominance threshold t_{dom} determines the corrective mandate:

If $\Delta > t_{\text{dom}}$: **Agent Stabilization** If $\Delta < -t_{\text{dom}}$: **Structural Correction** If $|\Delta| \leq t_{\text{dom}}$: **Dual-Path**

A scalar risk score is reported for comparability:

$$\text{Risk} = 100 \times (\text{ASL} + \text{CV}) / 2$$

Normalization used for heterogeneous indicators

Operational datasets mix counts, rates, and percentages. To combine them, each raw metric x is transformed to a bounded scale using robust percentile min-max normalization:

$$N(x) = \text{clip}((x - Q_{0.05}(x)) / (Q_{0.95}(x) - Q_{0.05}(x)), 0, 1)$$

Where a higher raw value indicates greater capacity (e.g., available beds), a deficit form is used: **Def = 1 – N(x)**.

Simulation A: Australia (AIHW ED lower-urgency use + hospital resources)

Goal. Demonstrate StARS scoring on multi-year public hospital system pressure using emergency department (ED) utilization and baseline staffing capacity.

Input files (provided).

AIHW-PHC-22-Use-of-emergency-departments-for-lower-urgency-care-2017-18-to-2023-24.xlsx
hospital-resources-tables-2023-24.xlsx **Unit of analysis.** State or Territory × year (2017-18 through 2023-24, mapped to start-year 2017-2023).

Raw fields extracted and derived

From the AIHW ED workbook (Table 3, "All persons" rows) at PHN level and aggregated to state-year: Population: Pop Total ED presentations (count): ED All-hours lower-urgency presentations (count): LU Lower-urgency rate (per 1,000): LURate After-hours lower-urgency rate (per 1,000): AHLURate In-hours lower-urgency rate (per 1,000): IHLURate Aggregation to state-year: Counts (Pop, ED, LU) are summed across PHNs. Rates are population-weighted averages across PHNs. Derived quantities: ED intensity per 1,000: EDrate = $1000 \times \text{ED} / \text{Pop}$ Lower-urgency share: LUshare = LU / ED From the AIHW hospital resources workbook (2023-24 baseline capacity anchors): Total staff (average FTE): StaffFTE (Table 3.2) Number of public hospitals: PublicHosp (Table 4.2) (context indicator) Capacity rate: Staff per 1,000: StaffRate = $1000 \times \text{StaffFTE} / \text{Pop}$ Staff deficit proxy: StaffDef = $1 - \text{N}(\text{StaffRate})$

ASL and CV construction (Australia)

Normalized metrics: $n_ED = \text{N}(\text{EDrate})$ $n_AH = \text{N}(\text{AHLURate})$ $n_Leak = \text{N}(\text{LURate})$ $n_Share = \text{N}(\text{LUshare})$ $n_Def = 1 - \text{N}(\text{StaffRate})$ Channel composites used in the baseline run:

$$\text{ASL} = 0.6 \cdot n_ED + 0.4 \cdot n_AH$$

$$\text{CV} = 0.4 \cdot n_Leak + 0.3 \cdot n_Share + 0.3 \cdot n_Def$$

Interpretation: ASL rises with total ED throughput and after-hours strain. CV rises with "leakage" (lower-urgency utilization) and with capacity deficit.

Simulation B: England (NHS England KH03 Beds Open Overnight)

Goal. Demonstrate StARS scoring using a direct operational capacity signal: bed availability and occupancy.

Input files (provided). Four quarterly KH03 spreadsheets:

Beds-Open-Overnight-Web_File-Q1-2024-25-revised.xlsx

Beds-Open-Overnight-Web_File-Q2-2024-25.xlsx

Beds-Open-Overnight-Web_File-Q3-2024-25-revised.xlsx

Beds-Open-Overnight-Web_File-Q4-2024-25.xlsx **Unit of analysis.** NHS England region x quarter (Q1-Q4 2024-25). The "England" aggregate row is excluded.

Raw fields extracted and derived

From each file, sheet "Region by Sector", Total series: Available beds (Total): A Occupied beds (Total): O Percent occupied (Total): P These are already quarterly summary values in the published tables. No additional population denominators are required for the within-series normalization used here.

ASL and CV construction (England beds)

Normalized metrics: $n_O = N(O)$ $n_P = N(P)$ $n_A = N(A)$ Capacity deficit: $n_{Def} = 1 - n_A$ Baseline composites:

$$ASL = 0.5 \cdot n_P + 0.5 \cdot n_O$$

$$CV = 0.6 \cdot n_{Def} + 0.4 \cdot n_P$$

Interpretation: ASL rises with saturation (P) and with occupied volume (O). CV rises when availability is constrained (low A) and when saturation is high.

Simulation C: New Zealand (publicly funded hospital discharges and procedures)

Goal. Demonstrate StARS scoring on a complete national discharge/procedure summary without patient-level records.

Input files (provided). Zip archive: publicly-funded-hospital-data-2018-2019.zip We parsed the pipe-delimited tables: PubFund_DischargesAll.txt PubFund_DischargesInjury.txt PubFund_Procedures.txt **Unit of analysis.** DHB (District Health Board of residence) for FinancialYear = 20182019.

Raw fields extracted and derived

Discharges (all): Total discharges: $T = \sum \text{Discharges}$ Diagnosis complexity proxy: ICD subgroup count = number of unique ICDSubgroup with Discharges > 0 ICD chapter concentration (Herfindahl): $H^{\text{ICD}} = \sum p_c^2$, where p_c is share of discharges in ICDChapter c Injury discharges: Injury discharges: $I = \sum \text{Discharges Injury share: } S^{\text{inj}} = I / T$ Procedures: Total procedures: $P = \sum \text{Procedures}$ Procedure complexity proxy: procedure block count = number of unique BlockCode with Procedures > 0 Procedure chapter concentration (Herfindahl): $H^{\text{proc}} = \sum q_k^2$, where q_k is share of procedures in ACHIChapter k

ASL and CV construction (New Zealand DHBs)

Normalized metrics: $n_T = N(T)$ $n_P = N(P)$ $n_{\text{inj}} = N(S^{\text{inj}})$ $n_{\text{icd}} = N(\text{ICD subgroup count})$ $n_{\text{proc}} = N(\text{procedure block count})$ $n_H = N(H^{\text{proc}})$ Baseline composites:

$$\text{ASL} = 0.5 \cdot n_T + 0.3 \cdot n_P + 0.2 \cdot n_{\text{inj}}$$

$$\text{CV} = 0.35 \cdot n_{\text{icd}} + 0.35 \cdot n_{\text{proc}} + 0.15 \cdot n_H + 0.15 \cdot n_{\text{inj}}$$

Interpretation: ASL rises with discharge and procedure volume, plus acute injury burden. CV rises with diagnostic/procedural diversity (operational complexity) and with structural imbalance (procedure concentration).

Internal intervention simulation (applied to all datasets)

To demonstrate the corrective implication of dominance, each record is subjected to a rule-based intervention aligned with its mandate: **Agent Stabilization**: $ASL' = 0.85 \cdot ASL$, $CV' = CV$ **Structural Correction**: $CV' = 0.85 \cdot CV$, $ASL' = ASL$ **Dual-Path**: $ASL' = 0.90 \cdot ASL$, $CV' = 0.90 \cdot CV$ Post-intervention dominance and risk are recomputed:

$$\Delta' = ASL' - CV'$$

$$Risk' = 100 \times (ASL' + CV') / 2$$

This component is a controlled "what-if" demonstration of channel-specific correction rather than a claim of causal effect in the underlying health system.

Sensitivity analysis suite (hospital-only robustness runs)

To test stability, StARS was rerun under five scenarios per dataset: baseline ($t_{dom} = 0.10$) low_threshold ($t_{dom} = 0.05$) high_threshold ($t_{dom} = 0.15$) agent_heavy (shift weights toward ASL) structure_heavy (shift weights toward CV) Each sensitivity CSV reports ASL, CV, Δ , mandate, risk, and post-intervention values for every record under each scenario.

Reproducibility notes

All outputs in this report were generated directly from the provided spreadsheets and text files. The CSV outputs are designed to be imported into the StARS tool as precomputed channel values (ASL, CV) or used as an external scoring benchmark. If the tool supports component-level inputs, the normalized proxy metrics described above can be passed as the subcomponents feeding ASL and CV.

Key limitations (transparent)

These datasets are aggregated operational summaries; they do not include direct burnout, moral injury, policy contradiction counts, or control-plane incident logs. ASL and CV are therefore computed as proxy composites derived from throughput, capacity, complexity, and imbalance signals available in public reporting. Intervention simulations are illustrative and not causal claims; they show expected directional behavior if the dominant channel is targeted.