Sensitivity Analysis of Perceptual Stabilization under Historical Compression

A Multi-Coordinate Analysis of Recruitment, Stabilization, and Signal Support

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Abstract

This paper examines parameter sensitivity in a toy realization of perceptual stabilization under historical compression. The analysis uses the declared computational equations without redefining them and evaluates separate coordinates for route formation, stabilization level, perceptual-stabilization status, current-signal support, support discordance, selector–dominance alignment, and a restricted false-completion interpretation. Eight deterministic sensitivity families, three episode/state Monte Carlo strata of 20,000 cases each, and one 50,000-case parameter-family Monte Carlo study use declared ranges, seeds, denominators, and reporting rules. All four common-defined combinations of perceptual stabilization and signal support occur in every Monte Carlo family. In the multi-block isolation sweep, all 40,401 cases are support-discordant while only 30,301 receive the narrower false-completion flag, showing that support discordance and false completion are computationally non-identical in this realization. The results characterize only the declared equations and sampling laws. They do not provide empirical validation, prevalence estimates, universal parameter robustness, or probabilities for cognitive systems.

Keywords: perceptual stabilization; historical compression; recruitment; signal support; support discordance; sensitivity analysis; toy model; computational realization.

1 Analytic Target and Scope

Perceptual stabilization under historical compression is represented here through several computationally distinct coordinates rather than through one ordered outcome variable. The formal account distinguishes recruitment, perceptual formation, perceptual stabilization, and current-signal support over a route-qualified formed application [1]. The toy model described in [2] instantiates this architecture as a direct formal realization: a formed application is available only after synthetic compression provenance, recruitment, and formation are established, after which PercStab and SigSup are evaluated separately [3].

The present analysis asks how these coordinates respond to systematic variation in state variables, coupling coefficients, thresholds, and selector–dominance relations. The main targets are the existence of a formed route, stabilization level and positive stabilization status, current-signal support, the occurrence of both stabilization/support discordance directions, and the relation between support discordance and the narrower false-completion interpretation.

The computational dependency is:

$$\begin{aligned}\text{declared sensitivity design} &\longrightarrow \text{perceptual-stabilization model}\\ &\longrightarrow \texttt{evaluate_episode}\\ &\longrightarrow \text{sensitivity records.}\end{aligned}$$

The sensitivity study therefore varies inputs and parameters within the declared realization without introducing a second definition of perceptual stabilization.

2 Declared Design and Reproducibility Boundary

The sensitivity design fixes the ranges, seeds, case counts, anchors, distributions, and denominator rules used for the reported analyses. Alternative parameter ranges, sampling laws, or summary rules would define separate exploratory analyses rather than alter the results reported here.

2.1 Output record and denominators

Each evaluated case retains the input/state coordinates, parameter snapshot, compression-provenance record, route status, recruited-field size, formation selector, historical-dominance selector, stabilization score and level, PercStab, support threshold, SigSup, support discordance, completion-semantics gate, dominance condition, and FalseComp. These fields are retained so that joint outcomes and denominators can be evaluated without collapsing undefined states into negative classifications.

The analysis uses explicit denominators:

D_{all} all valid generated specifications in a declared family;

D_{route} cases whose route status is not unresolved;

D_{formed} cases with a formed perceptual application;

D_{stab} cases with defined stabilization level and PercStab;

D_{sup} cases with defined SigSup;

D_{joint} cases where both terminal classifiers are defined;

D_{FC} cases where the derived false-completion flag is defined.

Undefined status is never recoded as zero. In particular, a case with no positive compressed route contributes to D_{all} and D_{route}, but it does not thereby become a negative perceptual-stabilization or signal-support case.

In the specified realization, every formed record has defined PercStab, SigSup, support-discordance status, and FalseComp. Consequently, for every declared family in this report,

$$D_{\text{formed}} = D_{\text{stab}} = D_{\text{sup}} = D_{\text{joint}} = D_{\text{FC}}.$$

This equality is a property of the current computational realization, not an identity among the denominator definitions. The denominators remain separately named because another realization or an empirical implementation may preserve one definedness surface while leaving another unresolved.

3 Deterministic Sensitivity Families

All two-dimensional grids use endpoint-inclusive `numpy.linspace` with 201 values per axis. The one-dimensional partial-threshold study uses 351 values. Unless an axis explicitly varies a parameter, all other model parameters remain fixed.

3.1 State sensitivity: S1

S1 varies $\ell_t^{\text{toy}} \times r_t^{\text{toy}}$ over $[0,1]^2$ with one block and fixed $M = 0.55$, $P = 0.90$, and Sup $= 0.65$. Figure 1 shows that the current overload/resource coordinates affect multiple downstream boundaries without turning those boundaries into one regime variable. A no-route region remains explicitly undefined for the terminal coordinates, while formed cases occupy several joint stabilization/support classes.

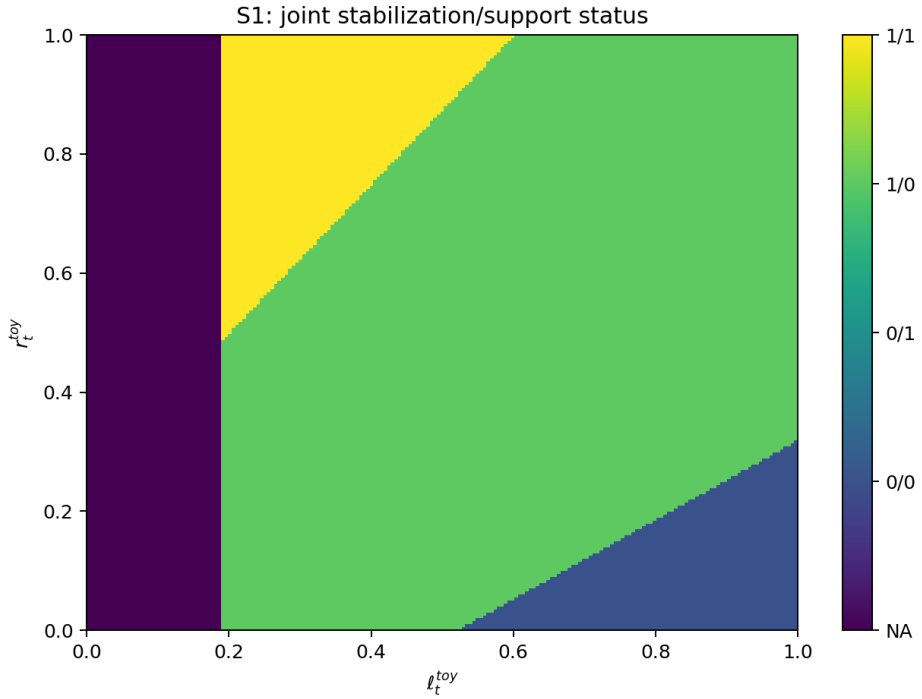


Figure 1: S1 joint PercStab / SigSup surface. NA denotes cases without a formed route and is not a negative model status. Integer display codes are figure-local only.

3.2 Historical dominance versus current-signal support: S2

S2 varies $P_t^{\text{toy}}(B_1) \times \text{Sup}_t^{\text{toy}}(B_1)$ with $\ell = 0.60$, $r = 0.40$, and $M = 0.55$. It provides the clearest deterministic visualization of the two-axis organization. The horizontal support transition and the distinct recruitment/stabilization boundaries along the dominance axis generate multiple common-defined combinations rather than a single ordering of "better" and "worse" perceptual regimes.

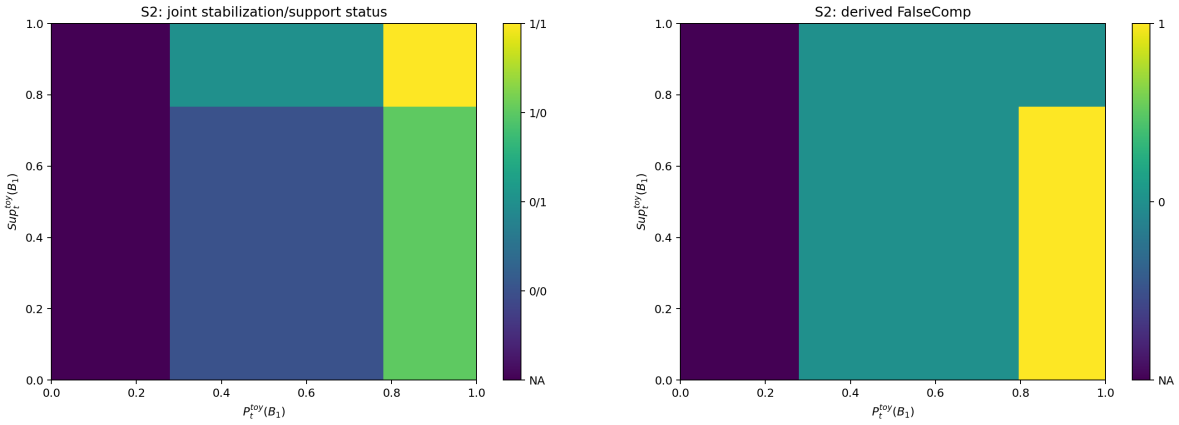


Figure 2: S2. Left: joint stabilization/support status. Right: the narrower derived false-completion surface. Support discordance can occur outside the false-completion region because the latter additionally requires its declared dominance/selection conditions.

3.3 Coupling sensitivity: S3a and S3b

The coupling analysis keeps recruitment, stabilization, and support effects explicitly separate. S3a varies recruitment coupling λ_L^{rec} against stabilization coupling w_ℓ^{stab}; S3b varies stabilization coupling against the overload contribution μ_L^{sup} to the support threshold. The two surfaces therefore test distinct coupling relations rather than treating them as one common overload-modulation axis.

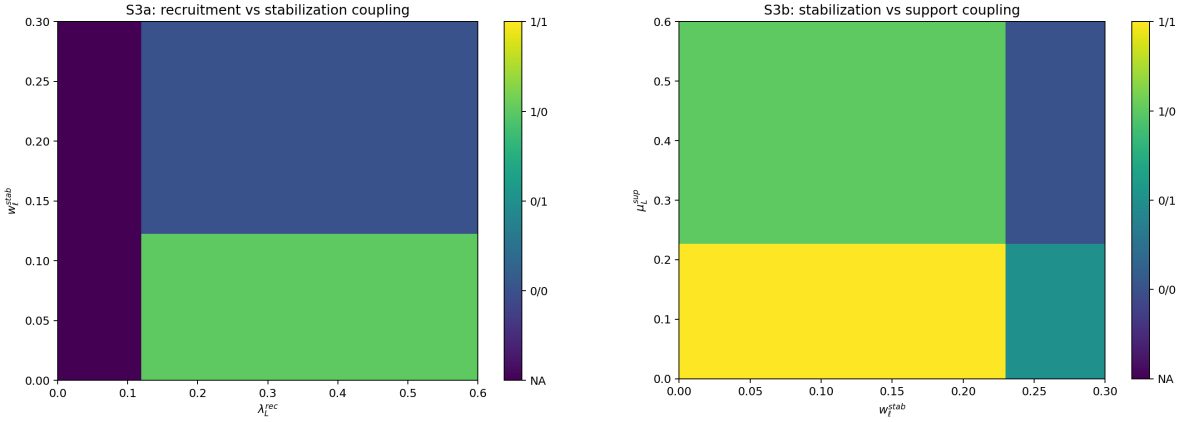


Figure 3: Separated coupling families. S3a (left) holds current-signal support below threshold throughout the formed region and therefore isolates recruitment/stabilization geometry. S3b (right) varies stabilization and support coupling independently. The simplicity of S3a is a result under the specified anchors, not a reason to retune them.

3.4 Threshold sensitivity: S4a, S4b, and S4c

Threshold sensitivity is evaluated on separately typed boundaries. S4a varies recruitment threshold τ_{match} against the positive stabilization threshold τ_{full}. S4b varies τ_{full} independently of the support threshold τ_{sup}. S4c varies only τ_{partial}, leaving $\tau_{\mathrm{full}} = 0.60$ fixed.

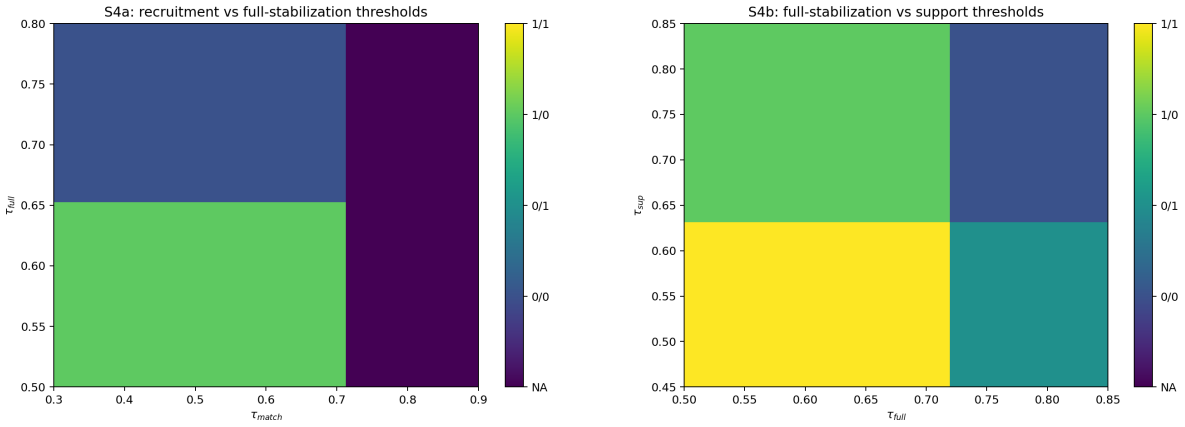


Figure 4: Threshold separation. S4a (left) tests recruitment versus positive stabilization. S4b (right) shows that the stabilization and current-signal-support boundaries can move independently.

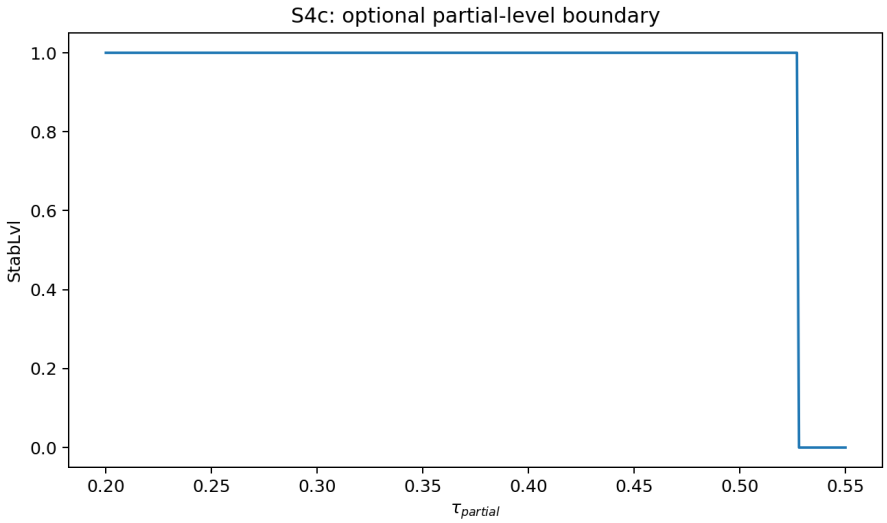


Figure 5: S4c varies only the optional partial-level threshold. The formed episode never becomes PercStab = 1; the sweep changes the local level-0/level-1 label while leaving the positive stabilization criterion unchanged.

3.5 Multi-block selector/dominance isolation: S5

S5 removes the single-block identity between formation selection and historical dominance. Across the entire 201×201 grid both blocks are recruited, PercStab = 1, and SigSup = 0 by analytic guards specified before execution. The only remaining difference relevant to the false-completion flag is the relation between the formation selector and the historical-dominance selector, with the dominance threshold satisfied whenever the selectors coincide under this construction.

All $40,401$ cells are therefore support-discordant. The selected and historically dominant blocks coincide in $30,301$ cells, and FalseComp = 1 occurs in exactly $30,301$ cells (75.00% of the declared grid). The remaining cells are support-discordant but false-completion negative.

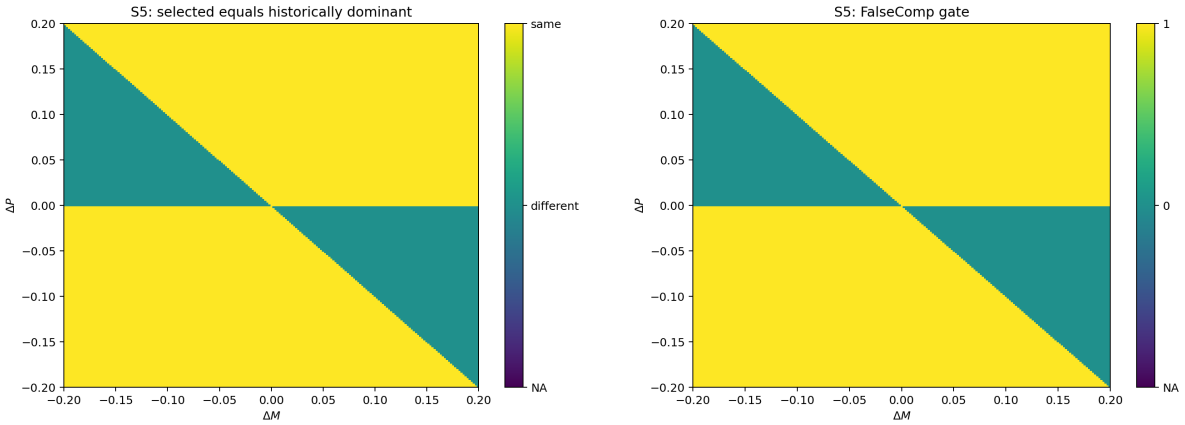


Figure 6: S5 selector/dominance isolation. The matching geometry of the two panels is intentional under the specified S5 construction: all other false-completion prerequisites are held positive, so the remaining gate is selector–dominance alignment. This equality is local to S5 and is not a general definition of false completion.

4 Monte Carlo Sensitivity

The random analyses answer two different questions and are not pooled into one robustness frequency.

4.1 MC-E: episode/state coverage under fixed model parameters

MC-E keeps the specified model parameterization fixed and samples episode coordinates independently from uniform $[0, 1]$ distributions. Three strata use 1, 2, and 3 blocks, each with $N = 20{,}000$ and a separately pre-specified seed. No missingness is injected. Consequently, downstream undefined values in MC-E arise from lack of a positive formed route rather than from artificial missing-data generation.

4.2 MC-P: parameter-family sensitivity under one fixed episode

MC-P keeps one episode fixed and samples nine declared parameter coordinates over pre-specified ranges with $N = 50{,}000$. It changes coefficients inside the specified equation family; it does not change the equations, selector semantics, partiality rules, or formal status definitions. It therefore asks how the fixed episode is partitioned under a declared parameter-family distribution, not how frequently cognitive systems occupy those states.

Family	N	Formed	PercStab =1	SigSup =1	Discordant	FalseComp	FC | discordant	Sel.=dom.
MC-E1 (1 block)	20000	47.72	50.28	26.24	36.09	15.33	42.48	100.00
MC-E2 (2 blocks)	20000	72.09	56.73	26.71	40.68	17.97	44.17	95.13
MC-E3 (3 blocks)	20000	85.06	64.05	27.51	45.56	21.03	46.15	90.60
MC-P	50000	71.97	40.90	32.10	27.68	23.05	83.26	100.00

Table 1: Monte Carlo summaries in percent. Formed uses D_{all}; stabilization and support use their defined denominators; discordance uses D_{joint}; FalseComp uses D_{FC}; the conditional column uses support-discordant cases; selector equality uses formed records with both selectors defined. These percentages are properties of the declared sampling laws only.

The fixed-parameter episode/state strata show a descriptive increase in formed-route proportion from 47.72% to 72.09% to 85.06% as the number of independently sampled blocks increases. Under

the same declared sampling design, support discordance among common-defined formed cases is 36.09%, 40.68%, and 45.56%, respectively. These are not prevalence estimates and do not establish a universal monotonic law in block count.

More importantly for construct separation, all four common-defined combinations occur in every Monte Carlo family:

Family	D_{joint}	0/0	0/1	1/0	1/1
MC-E1	9543	3595	1150	3444	1354
MC-E2	14419	4701	1538	5866	2314
MC-E3	17013	4582	1535	7751	3145
MC-P	35987	14474	6793	9962	4758

Table 2: Counts for PercStab / SigSup over the common-defined domain. The nonzero 0/1 and 1/0 cells directly demonstrate that the computational model does not definitionally identify stabilization with signal support.

The derived false-completion flag is narrower than support discordance in every Monte Carlo family. For MC-E1, MC-E2, and MC-E3, only 42.48%, 44.17%, and 46.15% of support-discordant cases, respectively, satisfy the additional false-completion gates. In MC-P the corresponding conditional proportion is 83.26%. The difference between these values is descriptive of the declared sampling designs and does not imply that one family is more psychologically realistic.

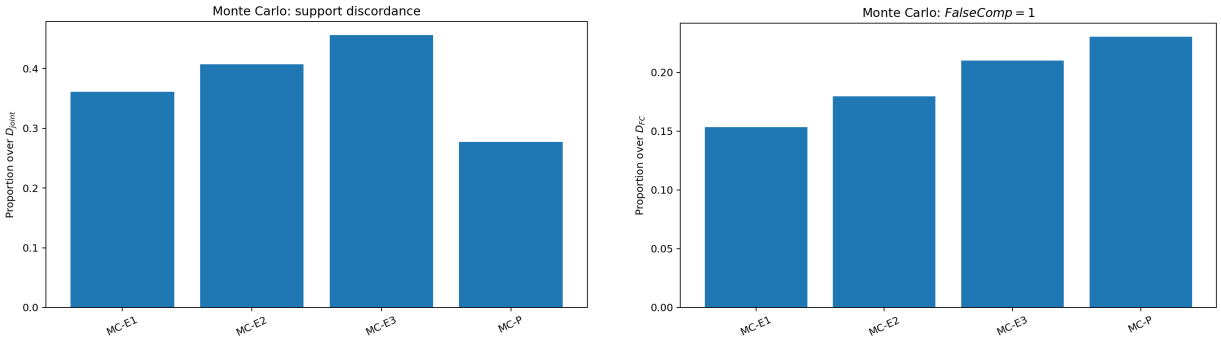


Figure 7: Monte Carlo proportions under their declared denominators. The left panel reports support discordance over D_{joint}; the right reports positive FalseComp over D_{FC}. These denominators are numerically equal in the specified realization but remain conceptually distinct. MC-E strata are shown separately; MC-P is a different parameter-family experiment and is not pooled with MC-E.

5 Reproducibility and Consistency Checks

The computational analysis includes checks for design consistency, definedness, result reproducibility, and traceability from generated cases to reported claims.

Declared anchors and non-retuning. Several deterministic families are intentionally simple under their declared anchors. S3a has negative signal support throughout its formed region; S4a likewise keeps support negative where formed; S4c changes only the optional level-0/level-1 distinction and never yields positive PercStab; S5 holds the entire grid in the PercStab $= 1, \text{SigSup} = 0$ fiber. These ranges and anchors isolate particular interfaces rather than maximize visual diversity.

Support discordance is not false completion. Support discordance is the primary joint status, whereas false completion is a narrower toy interpretation. S5 provides a controlled witness: support discordance is positive on all $40,401$ cells while false completion is positive on only $30,301$. S2 and all Monte Carlo families preserve the same non-identity.

Undefinedness is denominator-sensitive. No Monte Carlo family injects missing inputs, so `route_unresolved` does not arise in MC-E or MC-P. Cases with no positive compressed route nevertheless retain undefined downstream stabilization/support statuses and are excluded from the relevant terminal denominators. The absence of random missingness therefore does not turn undefined statuses into zeros.

Parameter-family typing. S3, S4, and MC-P vary coefficients only within the specified equation family. Recruitment coupling, stabilization coupling, and support-threshold modulation remain separately typed throughout the analysis.

Repeated execution. The deterministic families and Monte Carlo studies use fixed generation rules and declared random seeds. Repeated execution under the same equations, inputs, parameters, and seeds reproduces the reported counts, proportions, and figures. Parallel execution of the parameter-family study changes only execution order, not the resulting analysis records after their original ordering is restored.

Independent summary verification. Monte Carlo summaries can be recomputed directly from the generated analysis records. The recomputed denominators, 2×2 joint counts, support-discordance counts, false-completion counts, and conditional false-completion proportions reproduce the reported summaries. Positive FalseComp implies positive support discordance in every deterministic and Monte Carlo family, while support discordance is exactly the common-defined $\mathrm{PercStab} = 1, \mathrm{SigSup} = 0$ fiber in this realization.

Result derivation. Table values and figures are generated from the same analysis records used for the statistical summaries. Undefined cases retain an explicit NA display status and are not folded into negative classifications.

6 Limits

The analysis remains a toy-model sensitivity study. It does not establish empirical robustness, biological realism, clinical relevance, or universal parameter values. The Monte Carlo distributions are deliberate mathematical sampling laws, not fitted distributions of cognitive states. A nonzero sampled region does not establish empirical occurrence, and a high sampled proportion does not estimate prevalence.

The underlying toy model supplies historical compression as a synthetic positive construction premise [2]. The sensitivity analysis therefore cannot validate a real-world compression-to-current provenance relation. Likewise, the normalized overload/resource coordinates remain local realization coordinates, not universal scalar definitions of retained overload or processing resource.

Finally, support discordance and false completion remain structurally bounded labels. Neither entails semantic falsehood, hallucination, false belief, pathology, deception, or error with respect to an external environment. Such interpretations require an additional independently validated bridge.

7 Conclusion

This sensitivity analysis shows that the toy realization of perceptual stabilization under historical compression does not reduce to a single ordered outcome variable. Across the declared deterministic sweeps, recruitment and formation, perceptual stabilization, and current-signal support define distinct computational boundaries. In every Monte Carlo family, all four common-defined PercStab / SigSup combinations occur, including both discordant directions. The multi-block S5 sweep further shows that support discordance is broader than the optional false-completion interpretation: all 40,401 grid points satisfy PercStab = 1 and SigSup = 0, while only 30,301 satisfy the additional selector–dominance conditions for positive FalseComp. These findings establish separability within the declared computational realization and sampling laws. They do not establish empirical prevalence, biological validity, or universal parameter robustness across cognitive systems.

References

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