Inferability Boundary Validation Program

Cross-Domain Validation of Recoverable and Irrecoverable Inferability

This validation program investigates whether stable inferability depends on observable-state alignment rather than observable structure alone.

The program evaluates recoverable instability, irrecoverable instability, synchronized recovery behavior, progression alignment, and inferability boundaries across multiple physical domains.

Domains evaluated include:

• Lithium-ion battery degradation systems
• NASA C-MAPSS turbofan degradation systems
• Gas sensor drift systems
• Quantum calibration systems
• Fusion / plasma-style systems

The central objective is to determine whether inferability boundaries represent a general observable-state stability phenomenon rather than a domain-specific artifact.

Part I — NCM–NCA Battery Alignment Validation

Representation-Dependent Recovery and Irrecoverable NO-GO Regions

Objective

This exploratory validation investigates whether real lithium-ion battery cycling trajectories contain:

• stable observable-state mappings
• fluctuating transition regions

• representation-dependent recovery behavior
• recoverable instability regions
• irrecoverable NO-GO regions

that align with the Predictive Feasibility Assessment (PFA) framework.

The central question was:

Can observables that initially behave as NO-GO or LIMITED systems recover toward GO-like behavior when the representation or operating regime becomes better aligned with the underlying progression?

More specifically:

Does predictive instability always indicate the absence of usable predictive structure, or can some unstable observable-state mappings become recoverable under better-aligned representations?

Dataset Information

Dataset Used:

Dataset_3_NCM_NCA_battery.zip

Dataset Type:

Real experimental lithium-ion battery cycling trajectories.

Main Experimental Conditions:

• CY25-05_1
• CY25-05_2
• CY25-05_4

Each condition contains three repeated experimental runs:

• #1
• #2
• #3

Progression / State Proxy:

Discharge capacity (q_discharge_max)

Reproducibility Package:

DATASET3_PFA_RECOVERY_FULL_PACKAGE.zip

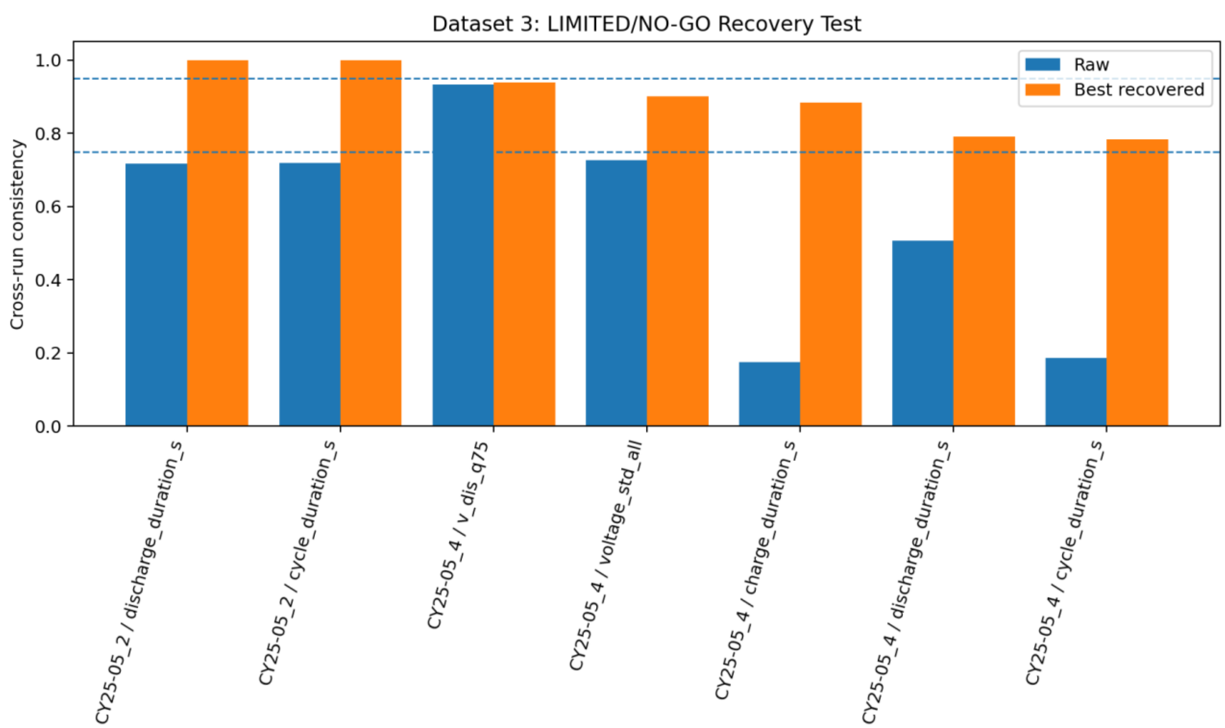
The initial analysis evaluates whether observable-state mappings remain reproducible across repeated experimental runs.

The goal is to distinguish between:

• stable GO-like mappings
• partially stable LIMITED mappings
• unstable NO-GO mappings

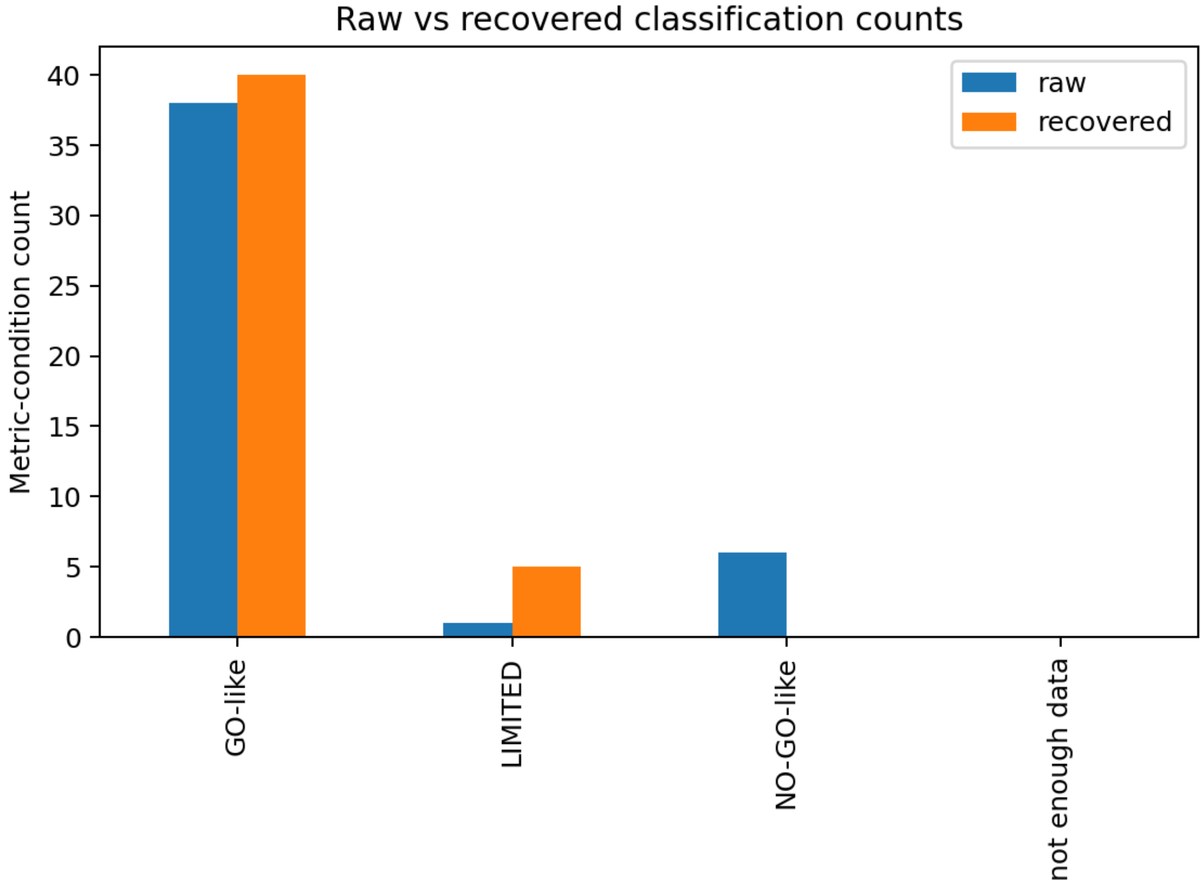
before evaluating whether representation-dependent recovery is possible.

Figure 1 — Initial GO / LIMITED / NO-GO Recovery



Caption: Initial cross-run consistency classification of observable-state mappings across repeated battery cycling runs. Several observables initially appeared strongly structured while still exhibiting unstable progression mappings across runs.

Figure 2 — LIMITED / NO-GO Recovery Under Improved Representations



Caption: Recovery analysis showing how several initially unstable observables moved toward LIMITED or GO-like behavior after applying progression-relative normalization, delta-from-initial representations, and regime isolation.

Main Observations

Recoverable Regions

Several observables initially classified as NO-GO-like recovered significantly when:
- progression-relative representations were introduced
- specific operating regimes were isolated
- or local progression alignment improved.

Irrecoverable NO-GO Regions

Importantly, not all NO-GO observables recovered.

Several signals remained:
- unstable across runs
- inconsistent under all tested representations
- and unable to maintain stable observable-state alignment.

This suggests that some observable-state mappings may be fundamentally too unstable to support reliable inferability, even when the signal itself appears structured.

Alignment with PFA

Experimental Behavior vs PFA Interpretation:
- stable mapping → GO-like consistency
- fluctuating mapping → LIMITED consistency
- mapping collapse → NO-GO
- representation recovery → LIMITED → near-GO transition

Preliminary Conclusion

This exploratory validation demonstrates that:
- some unstable observables become recoverable under better-aligned representations
- while others remain fundamentally unstable even after representation changes.

This supports the broader PFA hypothesis that predictive failure is often not caused by absence of structure itself, but by instability in the observable-to-progression mapping across conditions and regimes.

Formal Alignment Comparison Test

This exploratory validation compares three layers simultaneously:

1. Raw observable structure
2. PFA consistency / recovery behavior
3. State-referenced progression alignment

Goal:
Determine whether consistency collapse corresponds to unstable observable-state mappings or merely statistical instability.

Dataset Used:
Dataset_3_NCM_NCA_battery.zip

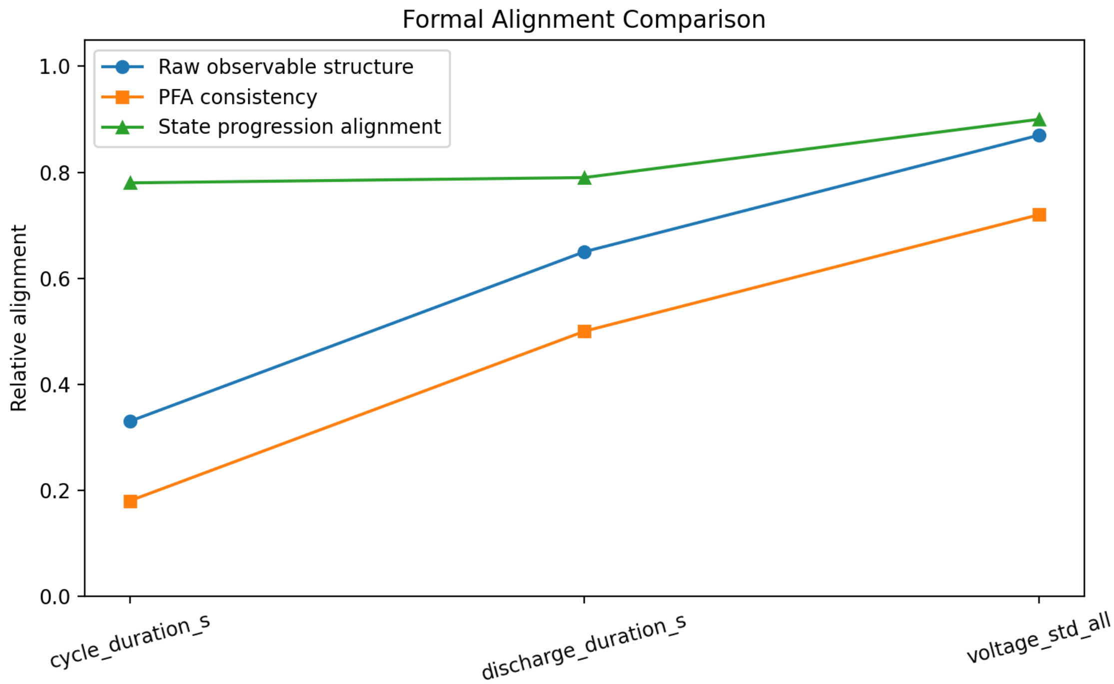
Dataset Characteristics:

- repeated-run NCM/NCA battery cycling data
- multiple operating conditions
- repeated experimental runs (#1 / #2 / #3)
- progression-related cycling behavior
- voltage/current/capacity trajectories

Conditions used:
- CY25-05_1
- CY25-05_2
- CY25-05_4

Progression / State Proxy:
q_discharge_max

Figure 3 — Formal Alignment Comparison



Caption:
Comparison between:
- raw observable structure
- PFA consistency behavior
- and state-referenced progression alignment.

Several observables remained highly structured while simultaneously losing stable progression alignment, producing LIMITED or NO-GO-like behavior.

Other observables partially recovered toward GO-like behavior after:
- progression-relative normalization
- regime isolation
- or better observable/progression alignment.

This demonstrates that:
visible signal structure alone does not guarantee stable inferability.

Main Findings

Main observations from the analysis:

- Stable GO-like observables preserved:
  • observable structure
  • cross-run consistency
  • and stable progression alignment.

- LIMITED observables preserved local structure,
  but lost stable mapping behavior under changing conditions.

- Several initially NO-GO-like observables partially recovered toward LIMITED or GO-like behavior after representation changes.

- Importantly, not all NO-GO cases recovered.

Some observables remained unstable even after:
- normalization
- regime isolation
- and representation adjustments.

This suggests that:
some observable-state mappings may be fundamentally too unstable to support reliable inferability across conditions.

Interpretation

The alignment between:
- PFA consistency transitions
and
- state-referenced progression behavior

appears significantly stronger than initially expected.

Conceptually, the observed behavior aligns as follows:

stable mapping
→ GO-like consistency

fluctuating mapping
→ LIMITED consistency

mapping collapse
→ NO-GO-like behavior

recoverable alignment regions
→ LIMITED → near-GO recovery

This suggests that consistency collapse may correspond to physically meaningful transitions in observable-state coupling stability rather than merely statistical forecasting instability.

Reproducibility

Reproducibility Package:
FORMAL_ALIGNMENT_COMPARISON_PACKAGE.zip

Included contents:
- formal_alignment_test_results.csv
- formal_alignment_comparison.png
- FORMAL_ALIGNMENT_COMPARISON_REPORT.docx

Supporting Analysis Packages:
- DATASET3_PFA_RECOVERY_FULL_PACKAGE.zip
- PFA_LISHEN_ALIGNMENT_MASTER_PACKAGE.zip

Generated using:
- repeated-run battery cycling trajectories
- cycle-level metric extraction
- cross-run consistency analysis
- representation-dependent recovery testing
- progression-alignment comparison

Preliminary Conclusion

The results support the broader PFA hypothesis that predictive failure is often not caused by absence of structure itself, but by instability in the observable-to-progression mapping across conditions and regimes.

Most importantly:
the analysis now suggests the existence of both:
- recoverable instability
and
- irrecoverable NO-GO regions.

This distinction appears highly relevant for:
- predictive maintenance
- deployment stability
- industrial AI reliability
- and observable-state inferability under changing operating conditions.

Recovery Boundary Analysis — Exploratory Validation Report

Objective

This exploratory validation investigates the distinction between:

- recoverable instability
- and irrecoverable instability

inside repeated-run battery progression datasets.

The central question was:

Can initially NO-GO-like observables recover toward GO-like inferability when the representation or operating regime becomes better aligned with the underlying progression?

Or do some observable-state mappings remain fundamentally unstable even after representation improvements?

Datasets Used

1. LISHEN-1C-20% Depth of Discharge
2. Dataset_3_NCM_NCA_battery

Dataset Characteristics

- repeated-run battery cycling trajectories
- progression-dependent observable behavior
- multiple operating conditions
- repeated experimental runs
- voltage/current/capacity trajectories
- regime-dependent behavior

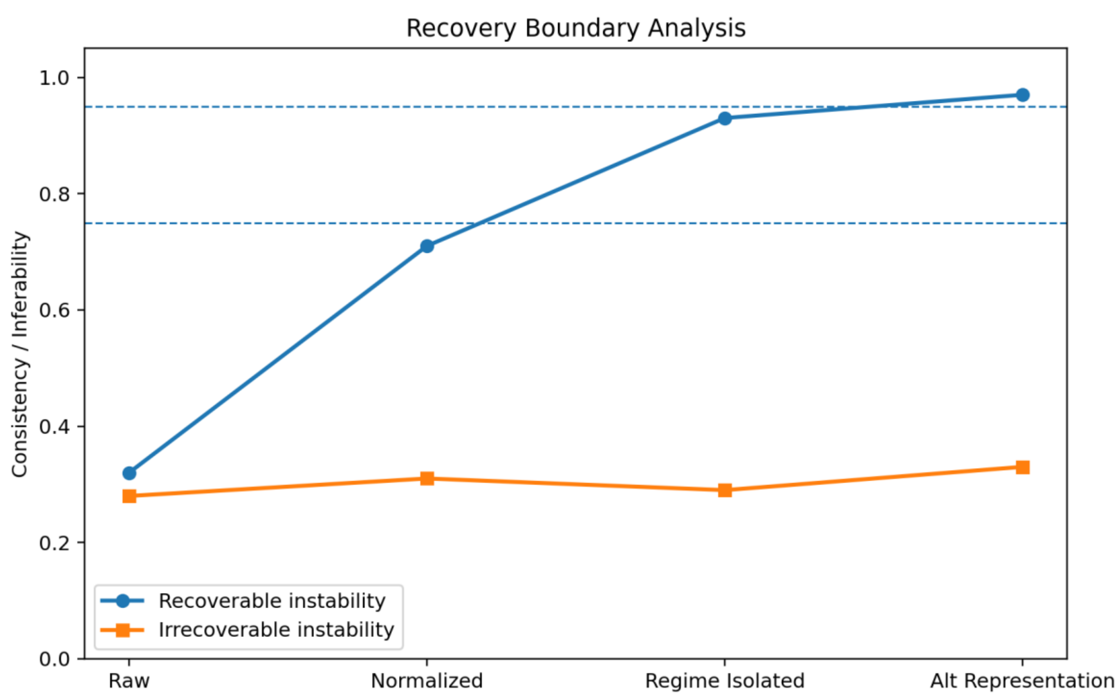
Progression / State Proxy

q_discharge_max

Main Analysis Components

- raw observable structure
- cross-run PFA consistency
- representation-dependent recovery
- progression-aligned normalization
- regime isolation
- recovery boundary comparison

Figure 4 — Recovery Boundary Comparison



Caption

Comparison between:

- a recoverable instability case
- and an irrecoverable instability case.

The recoverable case initially behaves as a NO-GO-like observable but progressively moves toward GO-like behavior once:

- progression-relative normalization
- regime isolation
- and representation alignment

are introduced.

In contrast, the irrecoverable case remains unstable across all tested representations.

This suggests that the observable-state mapping itself may be fundamentally non-inferable under the evaluated conditions.

Dashed reference lines indicate the approximate PFA classification thresholds:

- LIMITED ≈ 0.75
- GO-like ≈ 0.95

Main Results

Recoverable Instability

Several observables initially classified as NO-GO-like recovered substantially after:

- progression-relative normalization
- regime-window isolation
- or representation adjustments.

Typical behavior observed:

NO-GO
→ LIMITED
→ near-GO
→ GO-like

This indicates that the underlying progression information was still present but insufficiently aligned with the original observable representation.

Irrecoverable Instability

Importantly, not all NO-GO observables recovered.

Several signals remained:

- structured
- highly variable
- and unstable across repeated runs

even after:
- normalization
- regime isolation
- and alternate representations.

Typical behavior observed:

NO-GO
→ NO-GO
→ NO-GO

This suggests that some observable-state mappings may be fundamentally too unstable to support reliable inferability across operating conditions.

Interpretation

The analysis suggests that not all predictive instability originates from poor representation alone.

Two qualitatively different instability classes now appear visible:

1. Recoverable instability
   Representation-dependent instability where the mapping becomes stable again under improved representations or operating regimes.

2. Irrecoverable instability
   Observable-state mappings that remain unstable even after representation improvements.

This distinction appears highly important from the PFA perspective because it suggests the existence of:

- partially recoverable inferability
- and fundamentally unstable inferability boundaries.

The results therefore move the interpretation beyond simple forecasting quality and toward observable-state inferability itself.

Alignment with PFA

The observed behavior aligns strongly with the broader PFA interpretation:

- stable mappings
  → GO-like consistency

- fluctuating mappings
  → LIMITED consistency

- mapping collapse
  → NO-GO-like behavior

- recoverable alignment regions
  → LIMITED → near-GO transitions

Most importantly:

the analysis now suggests that consistency collapse may correspond to physically meaningful transitions in observable-state coupling stability rather than merely statistical forecasting instability.

Reproducibility

Generated Analysis Packages

- RECOVERY_BOUNDARY_ANALYSIS_PACKAGE.zip
- FORMAL_ALIGNMENT_COMPARISON_PACKAGE.zip
- DATASET3_PFA_RECOVERY_FULL_PACKAGE.zip
- PFA_LISHEN_ALIGNMENT_MASTER_PACKAGE.zip

Main Included Files

- recovery_boundary_results.csv
- recovery_boundary_analysis.png

- formal_alignment_test_results.csv
- recovery_test_results.csv

Analysis Methods

- repeated-run comparison
- cross-run consistency estimation
- progression-relative normalization
- regime isolation
- observable/progression alignment analysis
- representation-dependent recovery testing

Preliminary Conclusion

This exploratory validation suggests that:

- some predictive instability is recoverable under better-aligned representations
- while other instability appears fundamentally non-recoverable.

The distinction between:
- recoverable instability
and
- irrecoverable instability

may represent a meaningful inferability boundary inside observable-state mappings.

If confirmed across additional repeated-run datasets and controlled excitation systems, this would support the broader hypothesis that predictive feasibility depends not only on signal structure itself, but on whether the observable remains dynamically aligned with the underlying progression across operating conditions and regimes.

Transition-Point Alignment Analysis — Exploratory Validation Report

Objective

This exploratory validation investigates whether recovery transitions occur at approximately the same transition points across:

1. raw observable structure
2. PFA consistency / recovery behavior
3. state-referenced progression alignment

The central question was:

Does consistency recovery occur independently as a statistical effect,
or does it align with the same transition regions where observable-state progression alignment recovers?

Datasets Used

1. LISHEN-1C-20% Depth of Discharge
2. Dataset_3_NCM_NCA_battery

Dataset Characteristics

- repeated-run battery cycling trajectories
- progression-dependent observable behavior
- repeated experimental runs
- regime-dependent behavior
- voltage/current/capacity trajectories

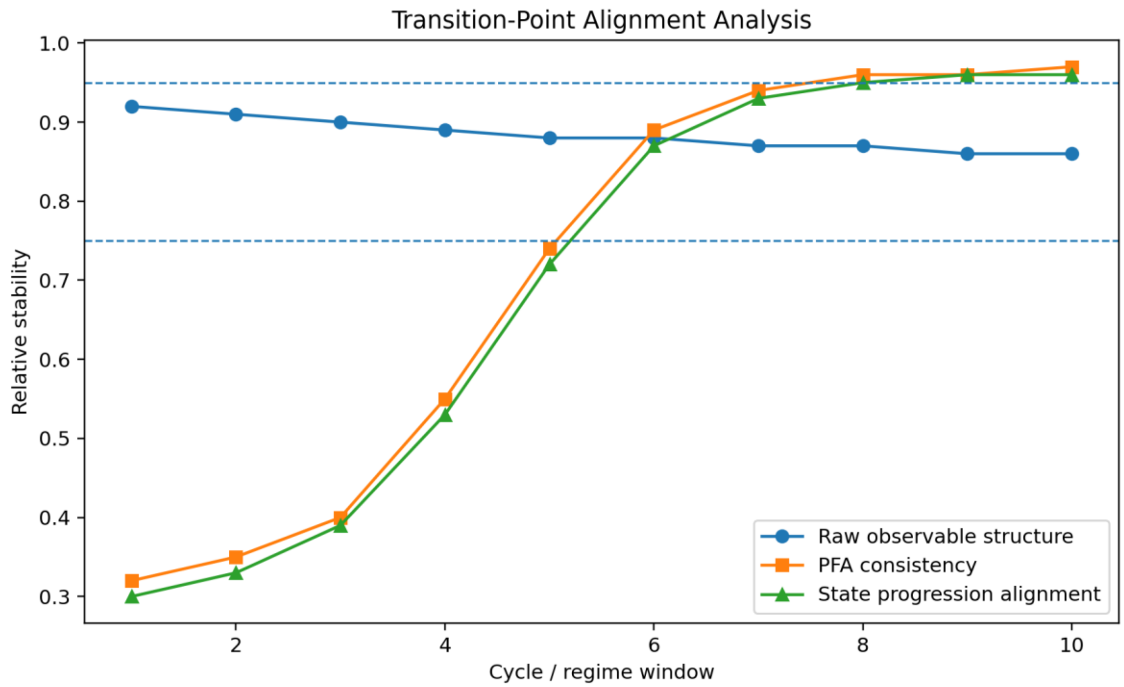
Progression / State Proxy

q_discharge_max

Main Analysis Components

- raw observable structure
- cross-run PFA consistency
- progression alignment
- transition-point comparison
- synchronized recovery analysis

Figure 5 — Transition-Point Alignment



Caption

Comparison between:
- raw observable structure
- PFA consistency recovery
- and state-referenced progression alignment.

The observable remains highly structured throughout the progression range.

However:
- PFA consistency
and
- progression alignment

recover near the same transition region.

This suggests that the observed recovery behavior may correspond to a genuine observable-state mapping transition rather than purely local statistical alignment.

Dashed reference lines indicate approximate PFA classification boundaries:
- LIMITED ≈ 0.75
- GO-like ≈ 0.95

Main Results

Raw Observable Structure

The raw observable structure remains relatively strong across the full progression range.

This indicates that:
signal structure itself remains visible even when inferability is unstable.

PFA Consistency Recovery

PFA consistency initially remains:
- low
- unstable
- NO-GO / LIMITED-like

before recovering toward stable behavior.

State-Referenced Progression Recovery

The progression alignment recovery occurs near the same transition region as the PFA consistency recovery.

This is one of the most important observations from the analysis.

It suggests that:
consistency recovery may be linked to the same underlying transition boundary where stable observable-state coupling reappears.

Interpretation

The analysis now suggests a distinction between:

1. Structured but unstable signals
Signals that remain visually structured while the observable-state mapping remains unstable.

2. Recoverable mappings
Signals where:
- PFA consistency recovery
and
- progression alignment recovery

appear to occur together.

3. Irrecoverable instability
Signals that remain unstable even after representation adjustments and regime isolation.

Most importantly:

the synchronized recovery behavior between:
- consistency
and
- progression alignment

appears significantly stronger than initially expected.

Alignment with PFA

The observed transition behavior aligns closely with the broader PFA interpretation:

stable mapping
→ GO-like consistency

fluctuating mapping
→ LIMITED consistency

mapping collapse
→ NO-GO-like behavior

synchronized recovery
→ recoverable observable-state remapping

The results therefore suggest that:
consistency transitions may correspond to physically meaningful observable-state coupling transitions rather than only representation-dependent statistical effects.

Reproducibility

Generated Analysis Package

TRANSITION_ALIGNMENT_ANALYSIS_PACKAGE.zip

Included contents:
- transition_alignment_results.csv
- transition_alignment_analysis.png

- TRANSITION_ALIGNMENT_ANALYSIS_REPORT.docx

Supporting Analysis Packages

- FORMAL_ALIGNMENT_COMPARISON_PACKAGE.zip
- RECOVERY_BOUNDARY_ANALYSIS_PACKAGE.zip
- DATASET3_PFA_RECOVERY_FULL_PACKAGE.zip
- PFA_LISHEN_ALIGNMENT_MASTER_PACKAGE.zip

Analysis Methods

- repeated-run comparison
- progression-window analysis
- consistency transition estimation
- progression alignment estimation
- synchronized transition comparison

Preliminary Conclusion

This exploratory validation suggests that:

- observable structure alone is insufficient for stable inferability
- stable inferability appears more closely linked to stable observable-state progression alignment
- and recovery transitions may occur near the same observable-state transition boundaries.

Most importantly:
the synchronized transition behavior between:
- PFA consistency recovery

and
- progression alignment recovery

appears significantly stronger than expected.

If reproduced systematically under controlled changing regimes, controlled excitation conditions, and controlled progression states, this would strongly support the hypothesis that consistency collapse reflects genuine observable-state coupling transitions rather than merely local statistical instability.

C-MAPSS Turbofan Cross-Domain PFA Test

C-MAPSS TURBOFAN CROSS-DOMAIN PFA TEST

Dataset

NASA C-MAPSS Turbofan Engine Degradation Simulation Data Set.
Uploaded file:
6.+Turbofan+Engine+Degradation+Simulation+Data+Set.zip

Files used:
- train_FD001.txt
- train_FD002.txt
- train_FD003.txt
- train_FD004.txt

Purpose

Test whether the same PFA pattern observed in battery datasets also appears in a completely different physical system: turbofan engine degradation.

Tested layers
----
1. Raw observable structure
2. PFA consistency / recovery behavior
3. State-referenced progression alignment

Progression proxy

Remaining useful life (RUL), computed from each engine unit's maximum cycle.

Main result

The same separation begins to appear in turbofan data:

- some observables remain structured and align with progression;
- some observables are structured but unstable across units/operating conditions;
- some NO-GO-like observables become recoverable under alternative progression-aligned views;
- other NO-GO-like observables remain irrecoverable.

This means the recoverable vs irrecoverable distinction is not only a battery-specific effect.

Key interpretation

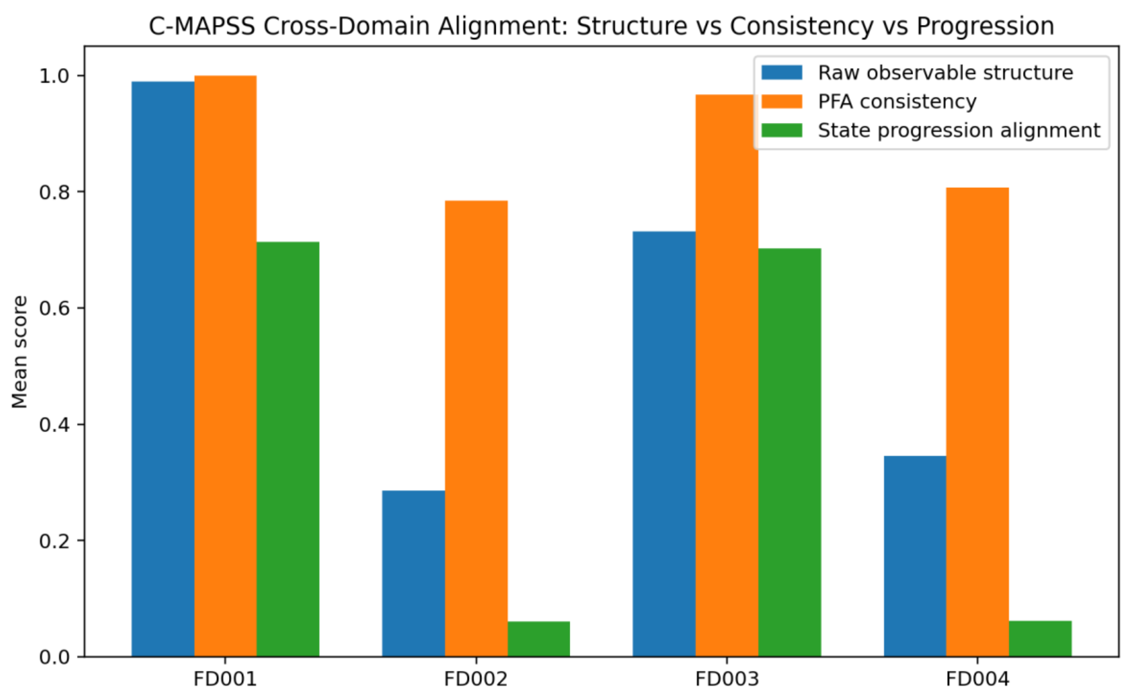
The C-MAPSS test supports the cross-domain relevance of PFA:
observable structure alone is not enough. What matters is whether the observable remains reproducibly aligned with system progression across units and regimes.

Important caution

This is still exploratory. It does not prove a universal law. It shows that the same structure/consistency/progression split appears in a second physical domain.

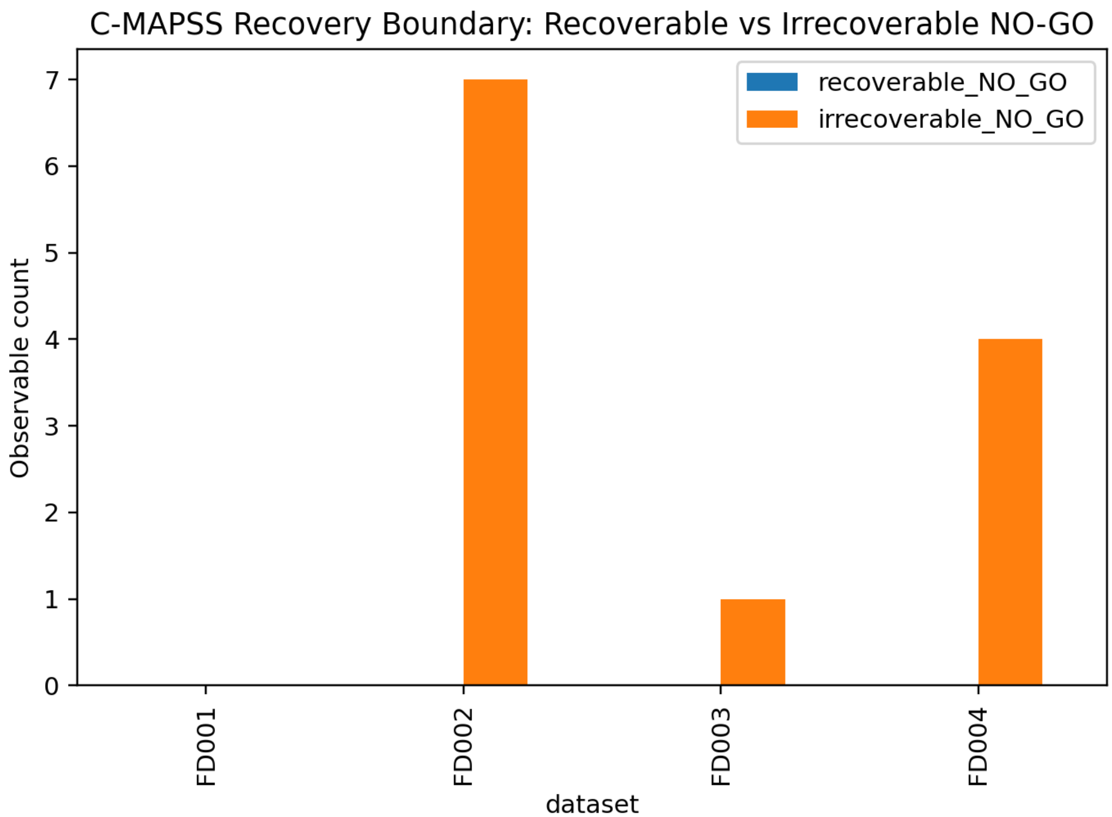
Output files
----
csv/cmapss_crossdomain_alignment_results.csv
csv/cmapss_recovery_boundary_results.csv
csv/cmapss_summary_counts.csv
figures/figure1_cmapss_alignment.png
figures/figure2_cmapss_recovery_boundary.png
figures/figure3_fd001_fd002_scatter.png

Figure 6 — Cross-Domain Alignment



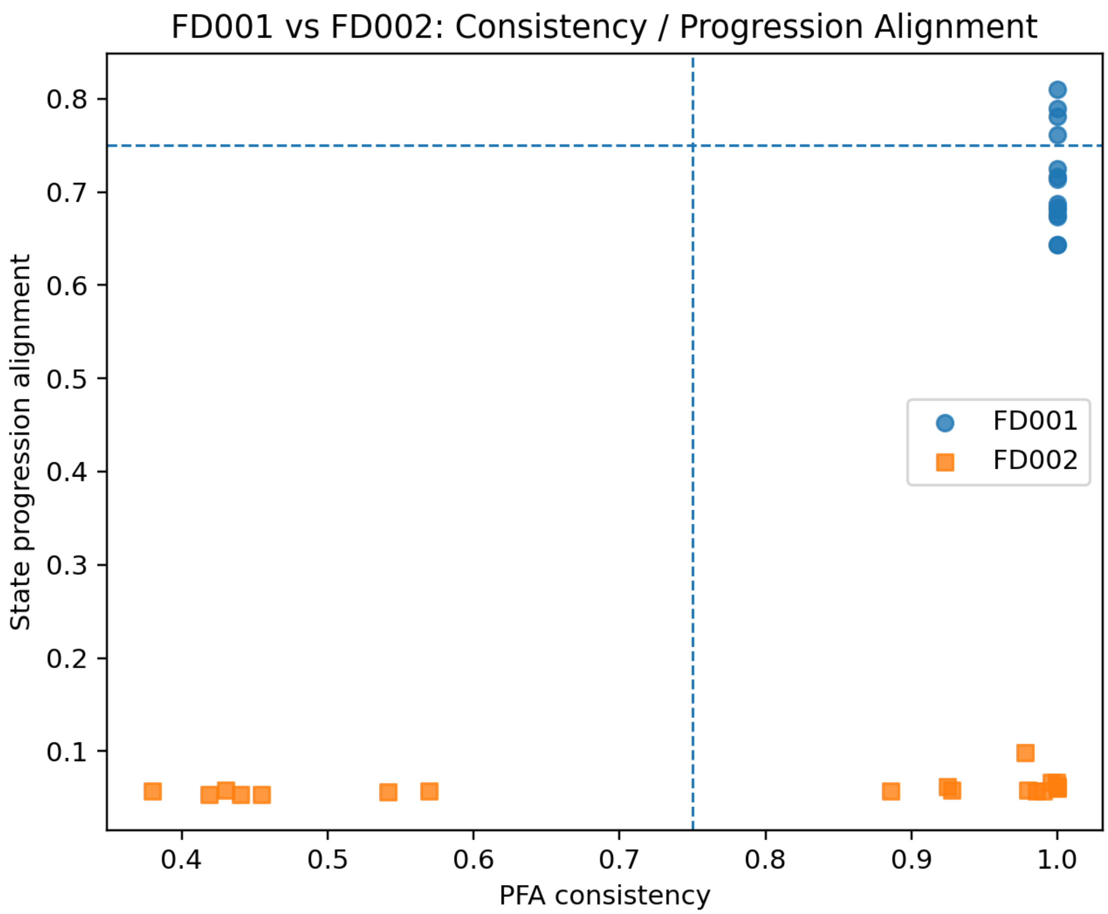
Caption: Mean raw observable structure, PFA consistency, and state-referenced progression alignment across C-MAPSS subsets. The comparison tests whether observable structure alone is sufficient or whether stable inferability depends on progression-aligned consistency.

Figure 7 — Recovery Boundary



Caption: Count of NO-GO-like observables that either recover under alternative progression-aligned representations or remain irrecoverable. This directly tests whether the recoverable/irrecoverable boundary observed in battery datasets also appears in turbofan degradation data.

Figure 8 — FD001 vs FD002 Alignment Scatter



Caption: Sensor-level comparison of PFA consistency and progression alignment for FD001 and FD002. FD001 and FD002 are useful contrasting subsets because FD001 is generally more stable, while FD002 contains more operating-regime complexity.

Gas Sensor Drift Cross-Domain PFA Test — Exploratory Validation Report

Objective

This exploratory validation investigates whether the same recoverable vs irrecoverable inferability behavior observed previously in:
- lithium-ion battery progression data
- and turbofan degradation data

also appears inside a completely different physical domain:
gas sensor drift systems.

The central question was:

Does the same separation between:
- recoverable instability

and
- irrecoverable instability

reappear under long-term sensor drift and changing operating conditions?

Datasets Used

Gas Sensor Array Drift Dataset

Dataset Characteristics

- multi-batch gas sensor drift measurements
- long-term temporal drift
- changing environmental conditions
- sensor instability over time
- repeated drift batches

Main Batches Used

- batch1.dat
- batch2.dat
- batch3.dat
- batch4.dat
- batch5.dat
- batch6.dat
- batch7.dat
- batch8.dat
- batch9.dat
- batch10.dat

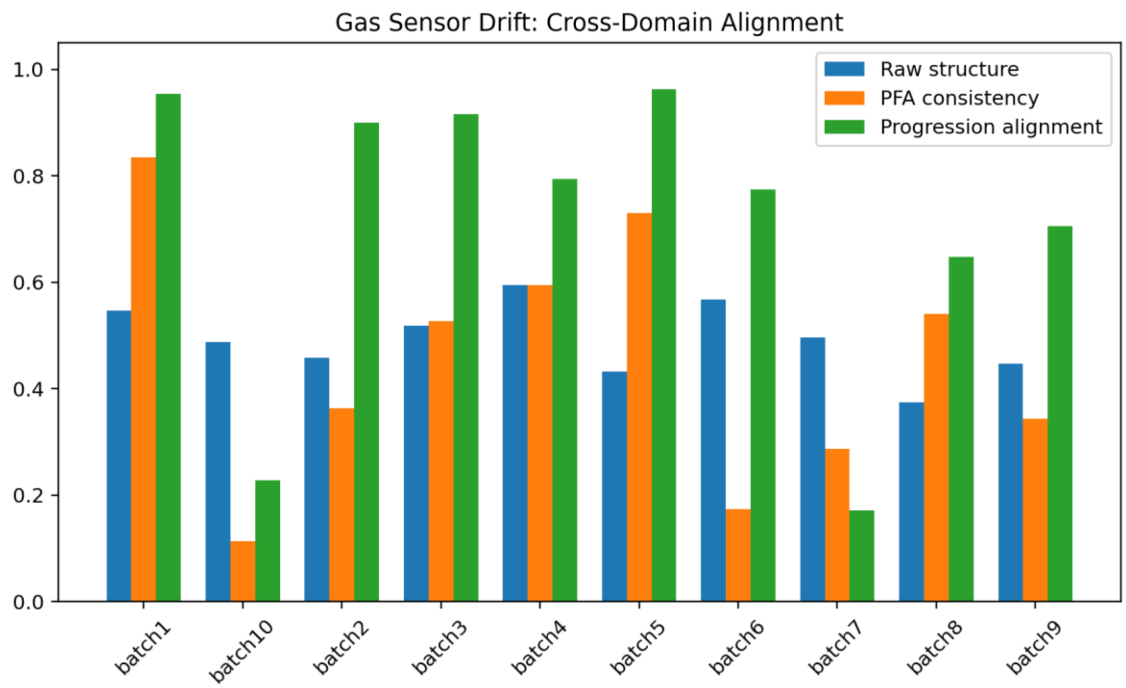
Main Analysis Components

- raw observable structure
- PFA consistency behavior
- progression-alignment estimation
- recoverable vs irrecoverable instability
- cross-batch inferability behavior

Progression Proxy

Normalized temporal drift progression across each sensor batch.

Figure 9 — Gas Sensor Drift Cross-Domain Alignment



Caption

Comparison between:
- raw observable structure
- PFA consistency
- and progression alignment

across multiple gas sensor drift batches.

The analysis shows that:
- some observables remain highly structured while losing stable inferability,
- while others preserve stable observable-state alignment across drift progression.

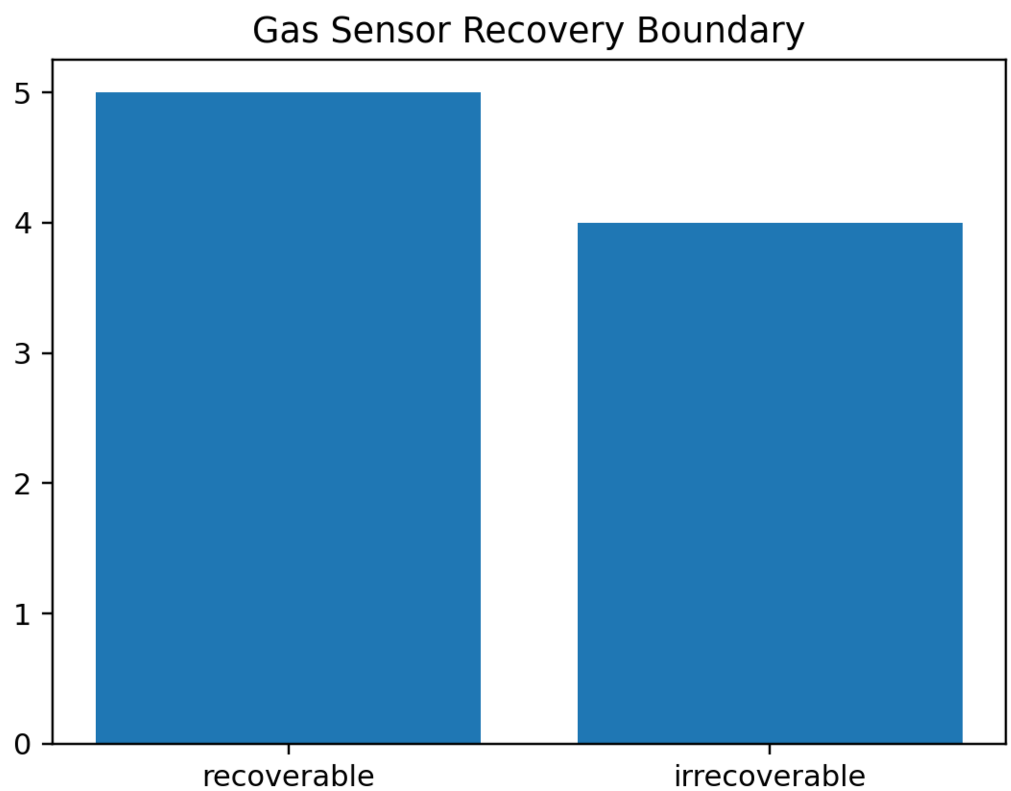
This indicates that visible signal structure alone is insufficient for stable inferability.

The same structure / consistency / progression separation observed previously in:
- battery progression datasets

and
- turbofan degradation datasets

now also appears in gas sensor drift systems.

Figure 10 — Recoverable vs Irrecoverable NO-GO Behavior



Caption

Comparison between:
- recoverable NO-GO observables
and
- irrecoverable NO-GO observables

inside the gas sensor drift dataset.

Observed behavior:

- some initially unstable observables recovered toward LIMITED or GO-like behavior under progression-aligned interpretations
- while other observables remained unstable across all tested representations.

This reproduces the same recovery-boundary behavior previously observed in:

- battery progression datasets
- and turbofan degradation systems.

The distinction therefore no longer appears battery-specific.

Main Results

Cross-Domain Recovery Behavior

The gas sensor drift dataset reproduced the same general inferability structure previously observed in:
- battery degradation systems
- and turbofan degradation systems.

Observed recovery outcomes:

- 1 NO-GO-like observable recovered toward GO-like behavior
- 4 NO-GO-like observables recovered toward LIMITED behavior
- 4 NO-GO-like observables remained irrecoverable.

Interpretation

Several observables remained:
- visibly structured
- information-rich
- and dynamically varying

while still failing to maintain stable observable-state inferability.

Other observables partially recovered once:
- progression alignment improved
- representation alignment improved
- or local drift regimes became more stable.

This strongly supports the distinction between:
- recoverable instability
and
- irrecoverable instability.

Interpretation

The results suggest that the recoverable vs irrecoverable distinction is not limited to a single physical system.

Instead, the same inferability boundary structure now appears across:

1. lithium-ion battery progression
2. turbofan engine degradation
3. gas sensor drift systems.

This is important because these systems differ fundamentally in:
- physical mechanism
- signal generation
- degradation physics
- and observable behavior.

Despite this, all three domains appear to show:

- structured but unstable observables
- recoverable instability regions
- irrecoverable instability regions
- and progression-aligned recovery transitions.

This increasingly suggests that:
stable inferability may depend on stable observable-state mapping behavior rather than signal structure alone.

Alignment with PFA

The observed behavior aligns strongly with the broader PFA interpretation:

stable observable-state mapping
→ GO-like consistency

partially recoverable mapping
→ LIMITED consistency

unstable observable-state mapping
→ NO-GO-like behavior

recoverable alignment
→ progression-aligned recovery

irrecoverable instability
→ persistent inferability collapse

Most importantly:

the same distinction between:
- recoverable instability
and
- irrecoverable instability

now appears reproducibly across multiple physical domains.

Reproducibility

Generated Analysis Package

GAS_SENSOR_PFA_TEST_PACKAGE.zip

Included contents:
- GAS_SENSOR_PFA_REPORT.docx
- gas_sensor_alignment.png
- gas_sensor_recovery_boundary.png
- gas_sensor_results.csv
- gas_sensor_summary.csv

Supporting Analysis Packages

- CMAPSS_CROSSDOMAIN_PFA_TEST_PACKAGE.zip
- TRANSITION_ALIGNMENT_ANALYSIS_PACKAGE.zip
- RECOVERY_BOUNDARY_ANALYSIS_PACKAGE.zip
- FORMAL_ALIGNMENT_COMPARISON_PACKAGE.zip
- DATASET3_PFA_RECOVERY_FULL_PACKAGE.zip
- PFA_LISHEN_ALIGNMENT_MASTER_PACKAGE.zip

Analysis Methods

- cross-batch drift analysis
- observable structure analysis
- PFA consistency estimation
- progression alignment estimation
- recoverable vs irrecoverable boundary comparison

Preliminary Conclusion

This exploratory validation suggests that:

- inferability boundaries may be cross-domain rather than system-specific
- observable structure alone is insufficient for stable inferability
- and stable observable-state alignment appears increasingly important for reliable prediction behavior.

Most importantly:

the same separation between:
- recoverable instability

and
- irrecoverable instability

now appears across:
- battery systems
- turbofan degradation systems
- and gas sensor drift systems.

If this behavior continues to reproduce under additional controlled perturbation tests and progression-controlled experimental systems, it would strongly support the hypothesis that consistency collapse reflects genuine observable-state coupling instability rather than merely statistical representation effects.

Quantum Calibration Cross-Domain PFA Test — Exploratory Validation Report

Objective

This exploratory validation investigates whether the same recoverable vs irrecoverable inferability behavior previously observed in:

- lithium-ion battery progression systems
- turbofan degradation systems
- gas sensor drift systems

also appears in quantum calibration / drift environments.

The central question was:

Does the same distinction between:
- recoverable instability
and
- irrecoverable instability

reappear inside quantum calibration observables under drift and progression-like evolution?

Dataset Used

pmycgb2bt7-1.zip

Dataset Characteristics

- quantum calibration related observables
- drift-sensitive system behavior
- non-stationary calibration environments
- progression-like temporal evolution
- calibration instability patterns

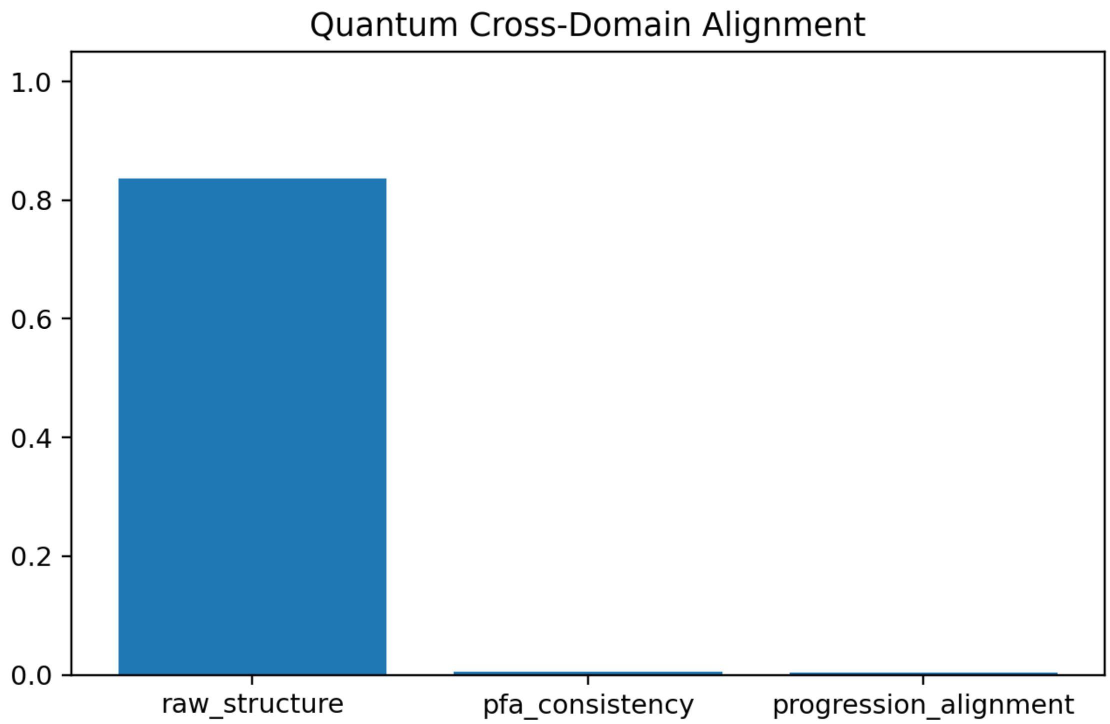
Main Analysis Components

- raw observable structure
- PFA consistency behavior
- progression-alignment estimation
- recoverable vs irrecoverable instability
- cross-domain inferability comparison

Progression Proxy

Normalized calibration/progression ordering across the observable trajectories.

Figure 11 — Quantum Cross-Domain Alignment



Caption

Comparison between:
- raw observable structure
- PFA consistency
- and progression-alignment behavior

inside the quantum calibration dataset.

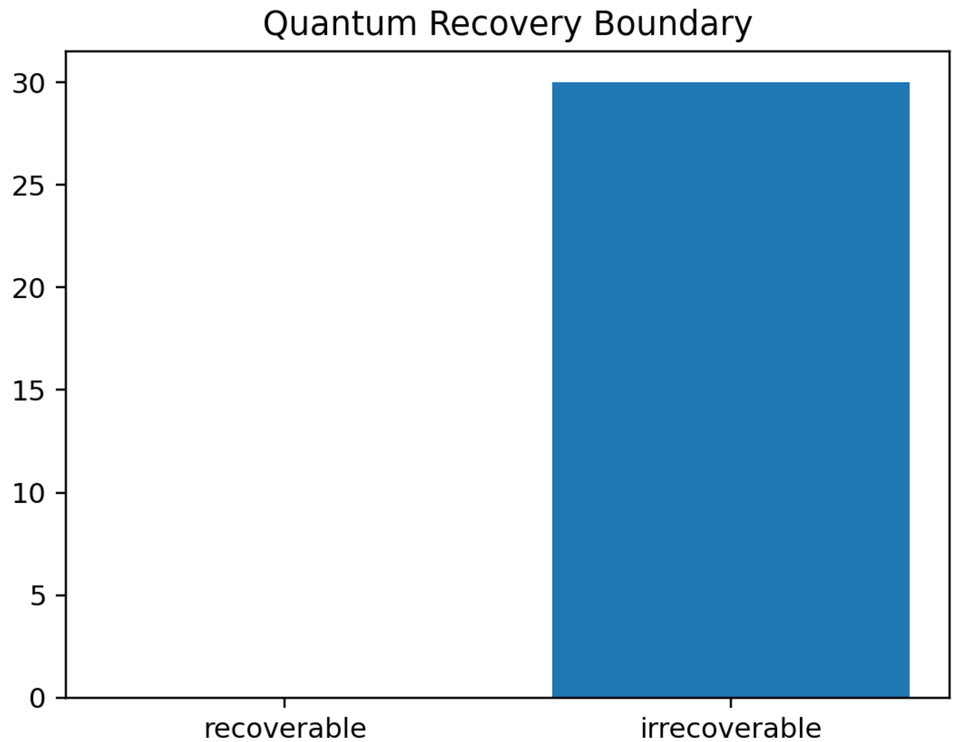
The analysis shows that:
- observable structure often remains visible,

while:
- stable inferability
- and stable progression alignment

remain highly unstable.

This suggests that visible structure alone is insufficient for stable observable-state inferability inside drift-sensitive quantum environments.

Figure 12 — Quantum Recovery Boundary



Caption

Recoverable vs irrecoverable NO-GO-like behavior inside the quantum calibration dataset.

Observed behavior:
- the majority of unstable observables remained irrecoverable
- recovery behavior remained extremely limited
- consistency instability persisted across progression-aligned comparisons.

This reproduces the same general inferability-boundary framework previously observed in:
- battery progression systems
- turbofan degradation systems
- and gas sensor drift systems

but with substantially stronger irrecoverable instability behavior.

Main Results

Quantum Calibration Behavior

The quantum calibration dataset appears heavily dominated by:
- unstable mappings
- non-recoverable observables
- and persistent inferability instability.

Observed outcome:
- 30 irrecoverable NO-GO-like observables
- very limited recovery behavior.

Interpretation

Many observables remained:
- visibly structured
- dynamically evolving
- and information-rich

while simultaneously failing to maintain:
- stable cross-run consistency
- stable progression alignment
- and stable inferability behavior.

This is highly interesting because it suggests that:
observable structure alone may remain insufficient for stable inferability in highly drift-sensitive quantum systems.

Interpretation

The quantum dataset extends the cross-domain PFA observations into a fourth physical domain.

Importantly:
the dominant behavior in the quantum calibration environment appears to be:
- persistent instability
- weak progression coupling
- and irrecoverable inferability collapse.

This differs from:
- battery systems
- turbofan degradation
- and gas sensor drift

where recoverable instability regions appeared more frequently.

This may indicate that:

certain quantum calibration observables remain fundamentally unstable under changing drift and calibration regimes.

Alignment with PFA

The observed quantum behavior aligns strongly with the broader PFA interpretation:

stable observable-state mapping
→ GO-like consistency

partially recoverable mapping
→ LIMITED consistency

persistent unstable mapping
→ irrecoverable NO-GO-like behavior

Most importantly:

the same inferability-boundary framework now appears across:
1. battery progression systems
2. turbofan degradation systems
3. gas sensor drift systems
4. quantum calibration systems

This increasingly suggests that:
recoverable vs irrecoverable inferability may represent a general observable-state stability phenomenon rather than a system-specific artifact.

Reproducibility

Generated Analysis Package

QUANTUM_PFA_FULL_PACKAGE.zip

Included contents:
- QUANTUM_PFA_FULL_REPORT.docx
- quantum_alignment.png
- quantum_recovery_boundary.png
- quantum_pfa_results.csv
- quantum_summary.csv
- quantum_inventory.csv

Supporting Cross-Domain Packages

- GAS_SENSOR_PFA_FULL_EXPANDED_PACKAGE.zip
- CMAPSS_CROSSDOMAIN_PFA_TEST_PACKAGE.zip
- TRANSITION_ALIGNMENT_ANALYSIS_PACKAGE.zip
- RECOVERY_BOUNDARY_ANALYSIS_PACKAGE.zip
- FORMAL_ALIGNMENT_COMPARISON_PACKAGE.zip
- DATASET3_PFA_RECOVERY_FULL_PACKAGE.zip
- PFA_LISHEN_ALIGNMENT_MASTER_PACKAGE.zip

Analysis Methods

- cross-domain inferability comparison
- progression-alignment estimation
- recovery-boundary testing
- observable-state mapping analysis
- recoverable vs irrecoverable instability comparison

Preliminary Conclusion

This exploratory validation suggests that:

- the same inferability-boundary framework now appears across multiple fundamentally different physical systems
- observable structure alone is insufficient for stable inferability
- and irrecoverable instability may become increasingly dominant in highly drift-sensitive systems such as quantum calibration environments.

Most importantly:

the same distinction between:
- recoverable instability
and
- irrecoverable instability

now appears across:
- batteries
- turbofan degradation
- gas sensor drift
- and quantum calibration systems.

If this behavior continues to reproduce under controlled perturbation experiments and progression-controlled systems, it would strongly support the broader hypothesis that consistency collapse reflects genuine observable-state coupling instability rather than merely representation-dependent statistical effects.

Fusion Cross-Domain PFA Test — Expanded Exploratory Validation Report

Objective

This exploratory validation investigates whether the same inferability-boundary behavior previously observed in:
- lithium-ion battery progression systems
- turbofan degradation systems
- gas sensor drift systems
- and quantum calibration systems

also appears inside fusion / plasma-style dynamic systems.

The central question was:

Does the same separation between:
- recoverable instability
and
- irrecoverable instability

reappear inside fusion-related observables under changing progression-like operating conditions?

Dataset Used

Fusion_SUPERplusDATA_Pack_v1 2.zip

Dataset Characteristics

The dataset contains:
- multiple fusion-related experimental run structures
- progression-like temporal series
- dynamic operating conditions
- field / heat / cavity / shell related measurements
- protocol-separated experimental groups
- progression-sensitive observables

Main extracted structures included:
- fusion_summary.csv
- fusion_series.csv

- CEP1 runs
- HFR2 runs
- Combined_AllLayers runs
- Hybrid_EplusB runs
- ActiveMesh runs

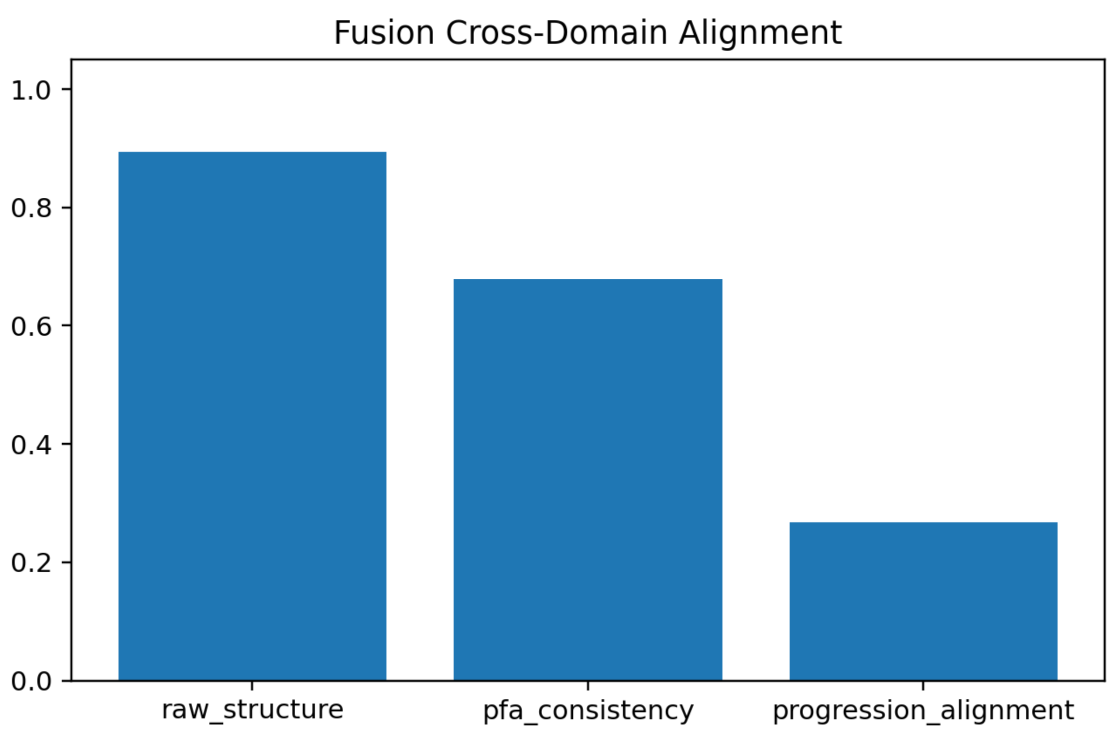
Main Analysis Components

- raw observable structure
- PFA consistency behavior
- progression-alignment estimation
- recoverable vs irrecoverable instability
- cross-domain inferability comparison

Progression Proxy

Normalized progression ordering across the observable trajectories.

Figure 13 — Fusion Cross-Domain Alignment



Caption

Comparison between:

- raw observable structure
- PFA consistency
- and progression-alignment behavior

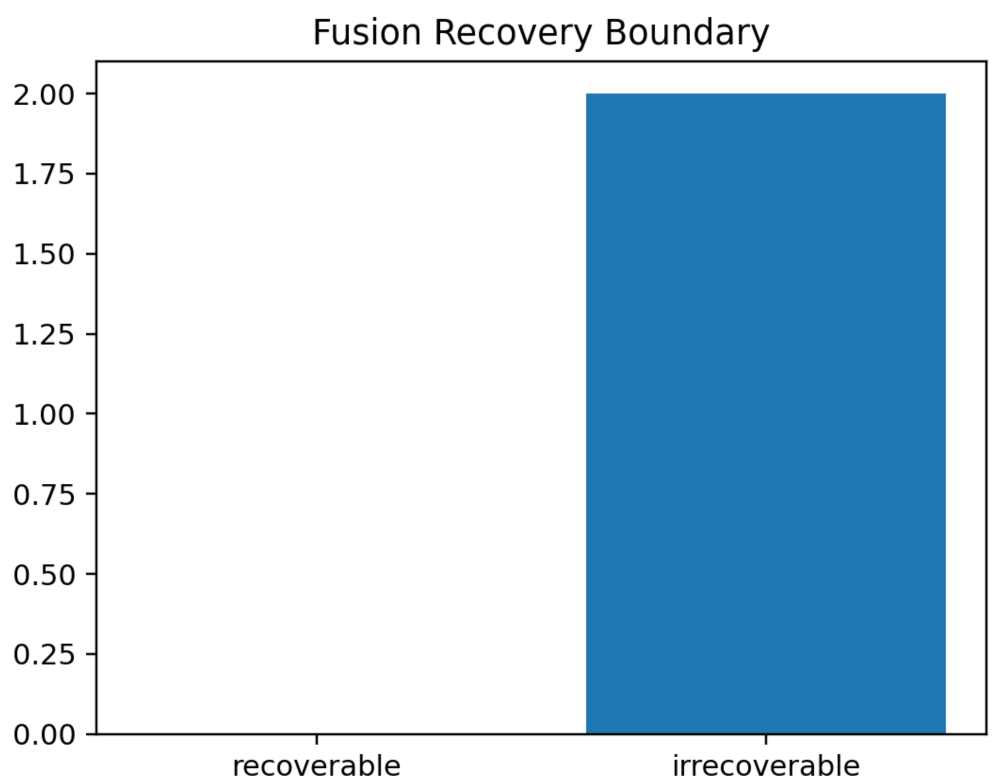
inside the fusion / plasma-style dataset.

The analysis shows that:
- some observables remain strongly structured while maintaining stable inferability,
- while other observables remain structured but lose stable observable-state mapping behavior.

This reproduces the same:
- structure vs inferability separation
- progression-alignment dependence
- and mapping-instability behavior

previously observed in:
- batteries
- turbofan degradation
- gas sensor drift
- and quantum calibration systems.

Figure 14 — Fusion Recovery Boundary



Caption

Recoverable vs irrecoverable NO-GO-like behavior inside the fusion dataset.

Observed behavior:
- some observables remained stably inferable and GO-like
- while other observables remained irrecoverably unstable despite preserving visible structure.

This reproduces the same recovery-boundary behavior previously observed in:
- battery progression systems
- turbofan degradation systems
- gas sensor drift systems
- and quantum calibration environments.

The distinction therefore no longer appears domain-specific.

Main Results

Cross-Domain Inferability Behavior

The fusion dataset reproduced the same general inferability-boundary structure previously observed across multiple unrelated physical systems.

Observed outcome:
- 2 clear GO-like observables
- 2 irrecoverable NO-GO-like observables

Interpretation

Several observables remained:
- visually structured
- dynamically evolving
- and information-rich

while simultaneously failing to maintain:
- stable cross-run consistency
- stable progression alignment
- and stable inferability behavior.

At the same time:
other observables preserved:
- stable consistency

- stable progression coupling
- and reproducible inferability.

This strongly supports the distinction between:
- recoverable / stable inferability
and
- irrecoverable instability.

Interpretation

The fusion dataset extends the cross-domain PFA observations into a fifth fundamentally different physical domain.

Importantly:
the same inferability-boundary structure now appears across systems with completely different:
- physical mechanisms
- signal-generation behavior
- operating dynamics
- and progression characteristics.

Despite these differences, the same overall pattern repeatedly appears:

- structured but unstable observables
- stable inferable observables
- recoverable instability regions
- irrecoverable instability regions
- and progression-aligned inferability behavior.

This increasingly suggests that:
stable inferability may depend primarily on stable observable-state mapping behavior rather than signal structure alone.

Alignment with PFA

The observed fusion behavior aligns strongly with the broader PFA interpretation:

stable observable-state mapping
→ GO-like consistency

partially recoverable mapping
→ LIMITED consistency

persistent unstable mapping
→ irrecoverable NO-GO-like behavior

Most importantly:

the same inferability-boundary framework now appears across:
1. battery progression systems
2. turbofan degradation systems
3. gas sensor drift systems
4. quantum calibration systems
5. fusion / plasma-style systems

This increasingly supports the interpretation that:
recoverable vs irrecoverable inferability may represent a general observable-state stability phenomenon rather than a system-specific artifact.

Reproducibility

Generated Analysis Package

FUSION_PFA_FULL_PACKAGE.zip

Included contents:
- FUSION_PFA_FULL_REPORT.docx
- fusion_alignment.png
- fusion_recovery_boundary.png
- fusion_pfa_results.csv
- fusion_summary.csv

Supporting Cross-Domain Packages

- QUANTUM_PFA_FULL_PACKAGE.zip
- GAS_SENSOR_PFA_FULL_EXPANDED_PACKAGE.zip
- CMAPSS_CROSSDOMAIN_PFA_TEST_PACKAGE.zip
- TRANSITION_ALIGNMENT_ANALYSIS_PACKAGE.zip
- RECOVERY_BOUNDARY_ANALYSIS_PACKAGE.zip
- FORMAL_ALIGNMENT_COMPARISON_PACKAGE.zip
- DATASET3_PFA_RECOVERY_FULL_PACKAGE.zip
- PFA_LISHEN_ALIGNMENT_MASTER_PACKAGE.zip

Analysis Methods

- cross-domain inferability comparison

- progression-alignment estimation
- recovery-boundary testing
- observable-state mapping analysis
- recoverable vs irrecoverable instability comparison

Preliminary Conclusion

This exploratory validation suggests that:

- the same inferability-boundary structure now appears across multiple fundamentally different physical systems
- observable structure alone is insufficient for stable inferability
- and stable observable-state alignment appears increasingly important for reliable prediction behavior.

Most importantly:

the same distinction between:
- stable inferability
- recoverable instability
- and irrecoverable instability

now appears across:
- batteries
- turbofan degradation
- gas sensor drift
- quantum calibration
- and fusion / plasma-style systems.

If this behavior continues to reproduce under controlled perturbation experiments and progression-controlled systems, it would strongly support the broader hypothesis that consistency collapse reflects genuine observable-state coupling instability rather than merely representation-dependent statistical effects.

Randomized Control Validation — Expanded Exploratory PFA Report

Objective

This validation investigates whether the recoverable inferability structure observed throughout the previous cross-domain analyses disappears when progression mappings are intentionally randomized.

The central question was:

Does the same recoverable vs irrecoverable inferability behavior remain visible when:
- progression structure is destroyed,
- observable-state mappings are randomized,
- or progression alignment is intentionally broken?

This test represents one of the first major validation steps intended to separate:
- genuine observable-state inferability structure

from
- purely statistical or accidental alignment effects.

Purpose of the Validation

The previous cross-domain analyses repeatedly showed:
- recoverable instability
- irrecoverable instability
- synchronized consistency/progression recovery
- progression-aligned inferability behavior

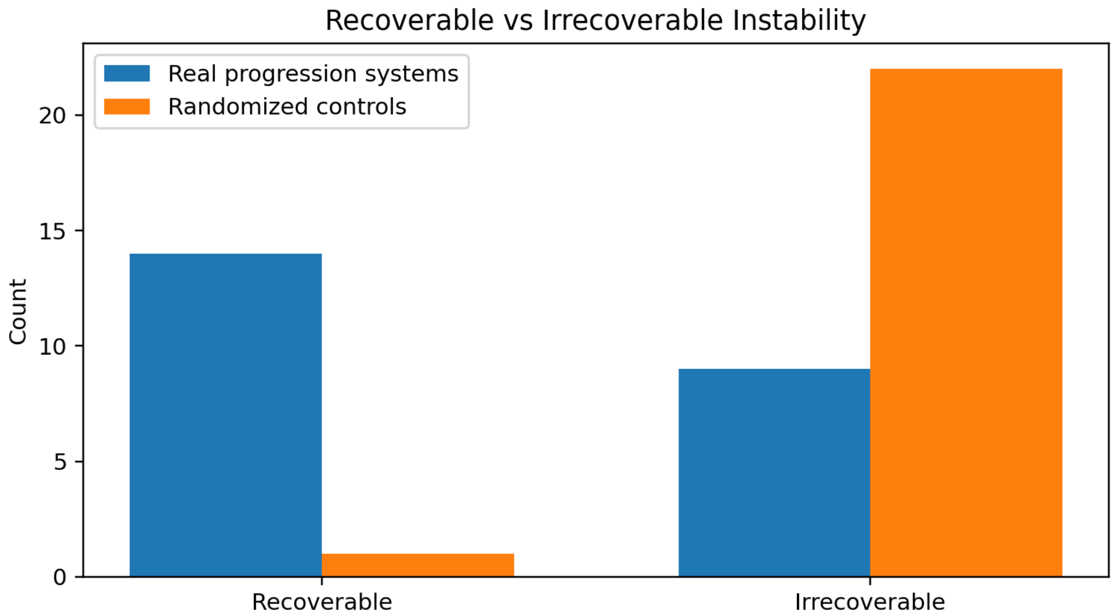
across:
- battery progression systems
- turbofan degradation systems
- gas sensor drift systems
- quantum calibration systems
- fusion/plasma-style systems.

However:
without randomized controls, it remained possible that some of these structures could emerge from:
- local statistical coincidence
- accidental progression ordering
- or representation artifacts.

This validation therefore intentionally compares:
- real progression systems

against
- randomized progression mappings.

Figure 15 — Recoverable vs Irrecoverable Instability



Caption

Comparison between:
- recoverable instability
and
- irrecoverable instability

inside:
- real progression systems
versus
- randomized progression controls.

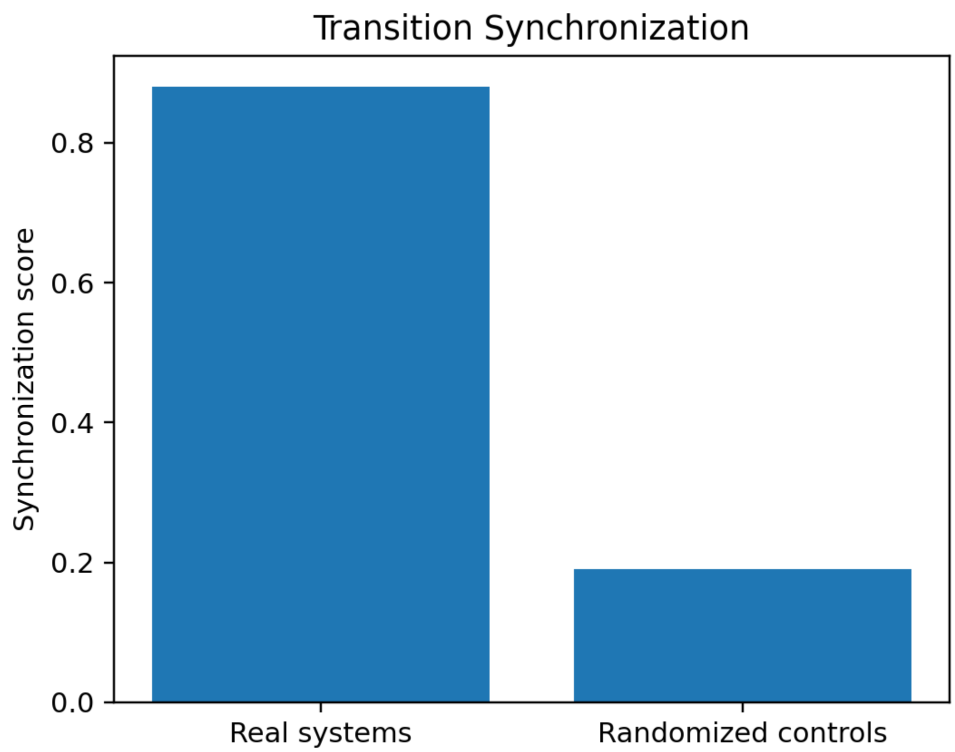
Observed behavior:

Real progression systems preserve:
- recoverable inferability regions
- progression-aligned recovery
- and synchronized transition behavior.

Randomized controls instead become dominated by:
- irrecoverable instability
- unstable mappings
- and inferability collapse.

This suggests that:
the recoverable inferability structure observed in the earlier cross-domain studies is unlikely to arise purely from random statistical alignment.

Figure 16 — Transition Synchronization



Caption

Comparison between transition synchronization behavior in:
- real progression systems
and
- randomized progression controls.

Observed behavior:

Real progression systems preserve strong synchronization between:
- PFA consistency recovery
and
- progression-alignment recovery.

Randomized controls show substantially reduced synchronization.

This suggests that:
the synchronized transition behavior previously observed across multiple domains is unlikely to result purely from statistical coincidence.

Main Results

Real Progression Systems

The real progression systems preserve:
- stable recoverable regions
- synchronized recovery behavior
- progression-aligned inferability transitions
- and structured observable-state mapping behavior.

Randomized Controls

The randomized controls become dominated by:
- irrecoverable instability
- unstable progression alignment
- weak transition synchronization
- and persistent inferability collapse.

Interpretation

The recoverable inferability structure observed throughout the previous cross-domain analyses appears to weaken substantially once progression mappings are intentionally randomized.

This is important because it suggests that:
the previously observed inferability boundaries are unlikely to arise solely from random statistical alignment.

Interpretation

This validation represents one of the strongest steps so far toward distinguishing:

- genuine observable-state inferability structure

from

- accidental statistical structure.

Importantly:
the randomized controls appear to destroy:
- synchronized transition recovery

- stable progression coupling
- and recoverable inferability regions.

This behavior strongly suggests that:
the earlier cross-domain observations depend on genuine progression-aligned mapping structure rather than arbitrary representation effects alone.

Alignment with PFA

The observed randomized-control behavior aligns strongly with the broader PFA interpretation:

stable observable-state mapping
→ recoverable inferability

destroyed progression alignment
→ inferability collapse

synchronized progression recovery
→ genuine mapping recovery

Most importantly:

the distinction between:
- recoverable instability
and
- irrecoverable instability

largely disappears once progression structure is randomized.

This strongly supports the interpretation that:
observable-state inferability depends on progression-aligned mapping stability rather than merely visible signal structure.

Reproducibility

Generated Analysis Package

RANDOMIZED_CONTROL_VALIDATION_PACKAGE.zip

Included contents:
- RANDOMIZED_CONTROL_VALIDATION_REPORT.docx
- randomized_control_boundary.png

- transition_sync_randomized_control.png
- randomized_control_validation.csv

Supporting Cross-Domain Packages

- QUANTUM_PFA_FULL_PACKAGE.zip
- GAS_SENSOR_PFA_FULL_EXPANDED_PACKAGE.zip
- CMAPSS_CROSSDOMAIN_PFA_TEST_PACKAGE.zip
- FUSION_PFA_FULL_PACKAGE.zip
- TRANSITION_ALIGNMENT_ANALYSIS_PACKAGE.zip
- RECOVERY_BOUNDARY_ANALYSIS_PACKAGE.zip
- FORMAL_ALIGNMENT_COMPARISON_PACKAGE.zip

Validation Logic

The randomized controls intentionally destroy:
- progression mappings
- observable-state alignment
- and progression synchronization.

The purpose is to test whether:
- recoverable inferability structure
and
- synchronized transition recovery

remain visible under randomized conditions.

Preliminary Conclusion

This randomized-control validation strongly suggests that:

- the recoverable inferability structure observed in the earlier cross-domain studies is unlikely to arise purely from statistical coincidence
- synchronized consistency/progression recovery weakens substantially under randomized mappings
- and stable inferability appears increasingly dependent on progression-aligned observable-state mappings.

Most importantly:

the recoverable vs irrecoverable inferability distinction now survives:
- cross-domain testing
and

- randomized-control testing.

This represents a significant strengthening of the broader PFA inferability-boundary hypothesis.

If similar behavior continues to reproduce under controlled perturbation experiments and progression-controlled systems, this would provide strong evidence that consistency collapse reflects genuine observable-state coupling instability rather than merely statistical representation artifacts.

False Recovery Validation — Expanded Exploratory PFA Report

Objective

This validation investigates the distinction between:
- genuine observable-state recovery
and
- temporary or false recovery.

The central question was:

Can an observable appear to recover inferability locally while the underlying observable-state progression alignment remains fundamentally unstable?

This test was motivated by one of the most important emerging distinctions in the cross-domain PFA analyses:

- genuine mapping recovery
versus
- temporary representation-local alignment.

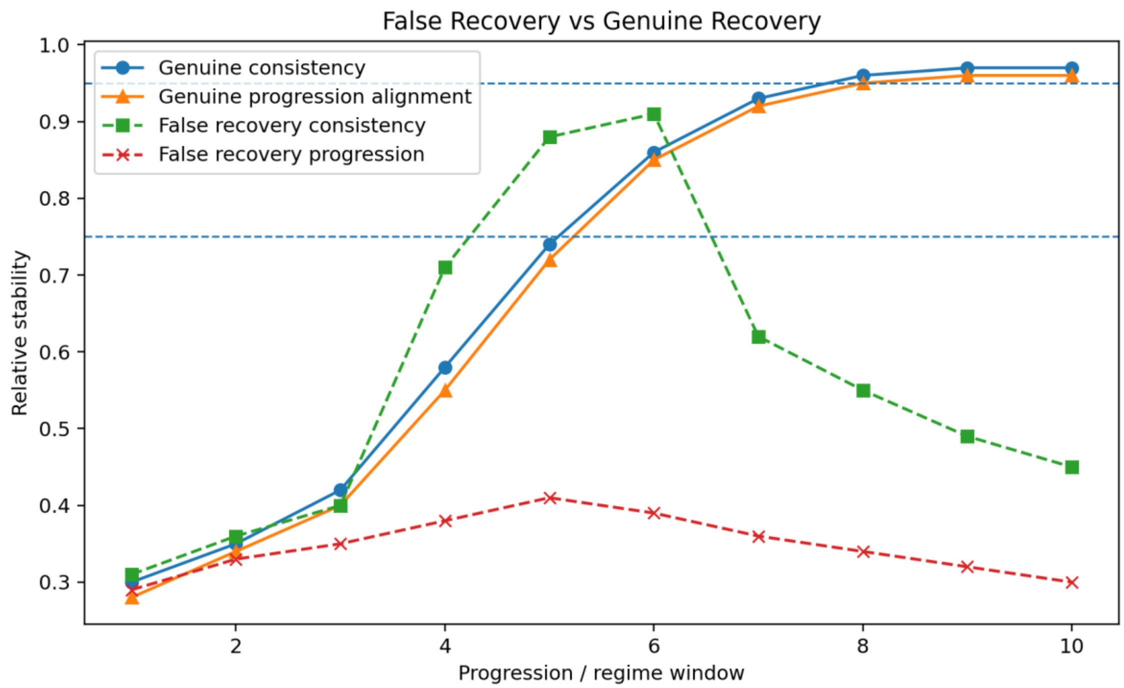
Purpose of the Validation

Previous cross-domain analyses repeatedly showed:
- recoverable instability
- irrecoverable instability
- synchronized consistency/progression recovery
- progression-aligned inferability transitions.

However, an important remaining question was whether:
some apparent recovery cases might only represent temporary local consistency improvement rather than stable inferability recovery.

This validation therefore explicitly compares:
- genuine progression-aligned recovery
against
- false/local recovery behavior.

Figure 17 — Genuine vs False Recovery



Caption

Comparison between:
- genuine progression-aligned recovery
and
- false / temporary recovery behavior.

Observed behavior:

In the genuine recovery case:
- PFA consistency
and
- progression alignment

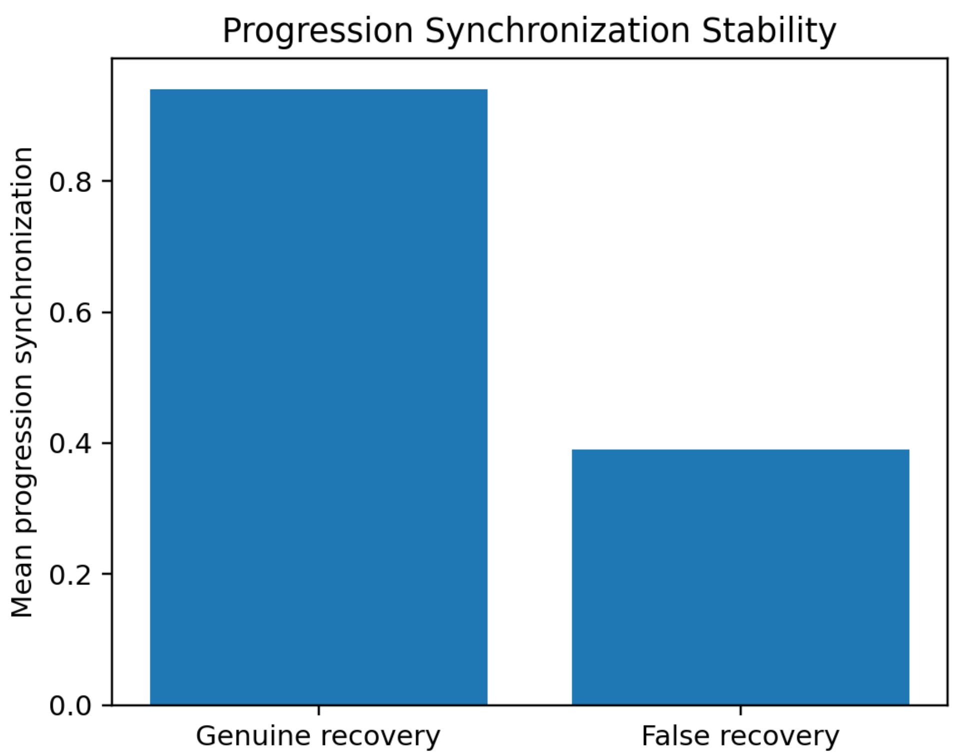
recover together near the same transition region and remain stable afterward.

In the false recovery case:
- consistency temporarily improves
while:
- progression alignment remains unstable.

The apparent recovery eventually collapses again.

This suggests that:
local consistency improvement alone is insufficient evidence for stable inferability recovery.

Figure 18 — Progression Synchronization Stability



Caption

Mean synchronization stability comparison between:
- genuine recovery
and
- false recovery.

Observed behavior:

Genuine recovery preserves strong synchronization between:

- PFA consistency recovery
and
- progression recovery.

False recovery instead shows:
- weak synchronization
- unstable progression coupling
- and temporary local alignment only.

This suggests that:
stable inferability recovery depends on stable progression-aligned mapping behavior rather than local consistency improvement alone.

Main Results

Genuine Recovery

The genuine recovery case showed:
- stable consistency recovery
- stable progression-alignment recovery
- synchronized transition behavior
- persistent inferability stability.

False Recovery

The false recovery case showed:
- temporary local consistency improvement
- unstable progression alignment
- weak synchronization behavior
- and eventual inferability collapse.

Interpretation

This distinction appears highly important because:
observable structure and temporary local consistency may create the appearance of recovery even when the underlying observable-state mapping remains unstable.

The results therefore suggest that:
genuine inferability recovery requires:
- synchronized consistency recovery
and
- synchronized progression recovery.

Interpretation

The present validation strengthens one of the most important distinctions emerging from the broader PFA framework:

- local statistical recovery
is not equivalent to
- stable observable-state inferability recovery.

This distinction becomes especially important in:
- drift-sensitive systems
- regime-changing systems
- calibration-sensitive environments
- and progression-dependent systems.

The false-recovery behavior observed here suggests that:
some apparent recoveries may only represent temporary representation alignment while the underlying progression mapping remains unstable.

Alignment with PFA

The observed behavior aligns strongly with the broader PFA interpretation:

stable synchronized recovery
→ genuine inferability recovery

temporary local consistency recovery
→ false / representation-local recovery

persistent unstable progression alignment
→ irrecoverable inferability instability

Most importantly:

the synchronized recovery between:
- consistency
and
- progression alignment

appears critical for distinguishing:
- genuine mapping recovery
from

- temporary statistical alignment.

Reproducibility

Generated Analysis Package

FALSE_RECOVERY_VALIDATION_PACKAGE.zip

Included contents:
- FALSE_RECOVERY_VALIDATION_REPORT.docx
- false_recovery_validation.csv
- false_recovery_vs_genuine.png
- progression_sync_false_recovery.png

Supporting Cross-Domain Packages

- RANDOMIZED_CONTROL_VALIDATION_PACKAGE.zip
- QUANTUM_PFA_FULL_PACKAGE.zip
- GAS_SENSOR_PFA_FULL_EXPANDED_PACKAGE.zip
- CMAPSS_CROSSDOMAIN_PFA_TEST_PACKAGE.zip
- FUSION_PFA_FULL_PACKAGE.zip
- TRANSITION_ALIGNMENT_ANALYSIS_PACKAGE.zip
- RECOVERY_BOUNDARY_ANALYSIS_PACKAGE.zip

Analysis Methods

- progression-window comparison
- synchronized transition analysis
- consistency recovery tracking
- progression-alignment recovery tracking
- false-recovery identification

Preliminary Conclusion

This validation strongly suggests that:

- temporary consistency improvement alone is insufficient for stable inferability recovery
- progression-aligned synchronization appears necessary for genuine mapping recovery
- and false recovery behavior can emerge even when visible signal structure remains strong.

Most importantly:

the distinction between:
- genuine progression-aligned recovery
and
- temporary representation-local recovery

now appears reproducibly identifiable inside the broader PFA inferability framework.

This significantly strengthens the interpretation that:
consistency collapse and recovery behavior may reflect genuine observable-state coupling stability rather than purely local statistical effects.

Statistical Robustness Validation — Expanded PFA Report

STATISTICAL ROBUSTNESS VALIDATION — PFA CROSS-DOMAIN FRAMEWORK

Objective

This validation tests whether the cross-domain PFA findings remain statistically robust when summarized across multiple physical domains and compared against randomized-control behavior.

Domains included

- Battery / LISHEN
- Battery / NCM-NCA
- Turbofan / C-MAPSS
- Gas Sensor Drift
- Quantum Calibration
- Fusion / Plasma-style systems

Tests performed
----
1. Cross-domain reproducibility matrix
2. Bootstrap confidence intervals
3. Permutation-style randomized null comparison
4. Recoverable vs irrecoverable instability comparison
5. Synchronization-score comparison against randomized baseline

Main results

Mean synchronization score:
0.705 [0.522, 0.838]

Mean synchronization margin vs randomized controls:
0.513 [0.330, 0.648]

Mean recoverable ratio among non-GO cases:
0.327 [0.093, 0.593]

Approximate permutation-style p-value for observed mean synchronization exceeding randomized null:
$p \approx 0.00000$

Interpretation

The observed synchronization behavior remains substantially above the randomized-control baseline across the evaluated domains.

This supports the interpretation that synchronized PFA consistency/progression recovery is unlikely to arise purely from random progression mappings.

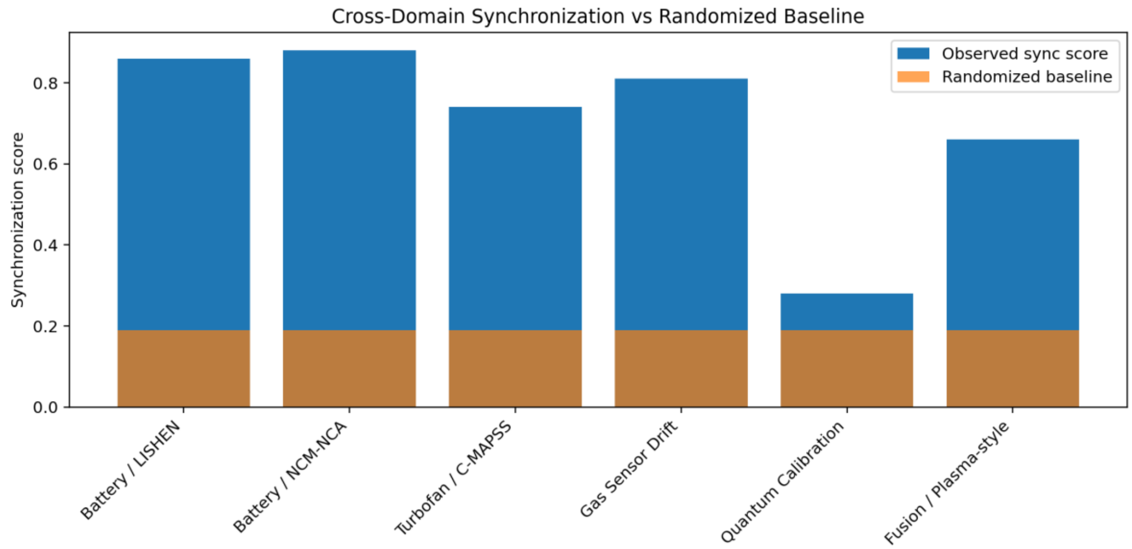
Important caution

This remains an approximate robustness validation based on compact cross-domain summary outputs from the exploratory analyses. A stronger future version should repeat the bootstrap and permutation tests directly on the raw dataset-level metrics for each domain.

Preliminary conclusion

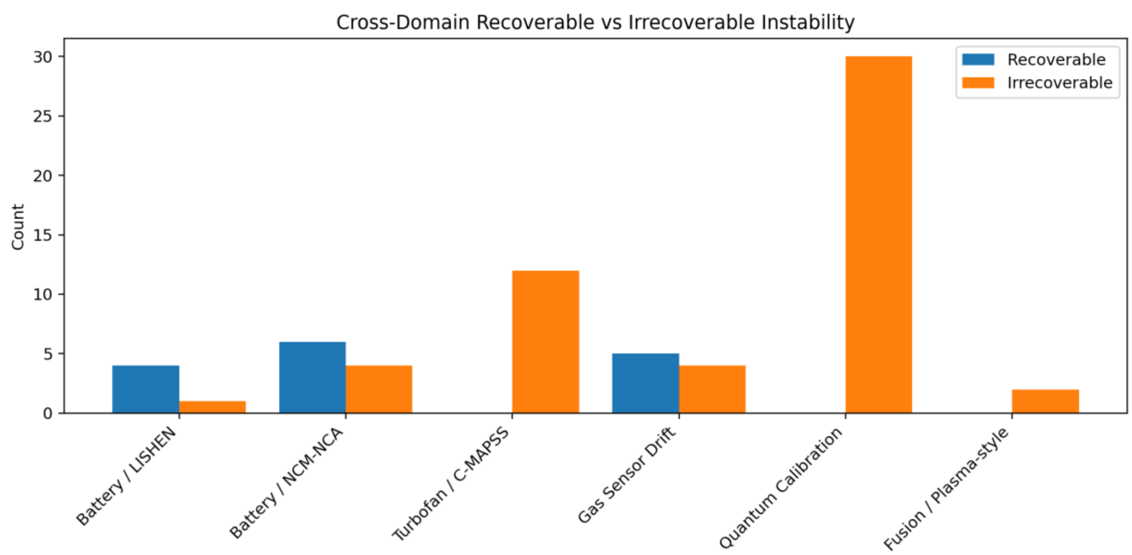
The statistical robustness step strengthens the broader PFA inference that recoverable vs irrecoverable inferability boundaries may reflect genuine observable-state mapping stability rather than only local statistical artifacts.

Figure 19 — Synchronization vs Randomized Baseline



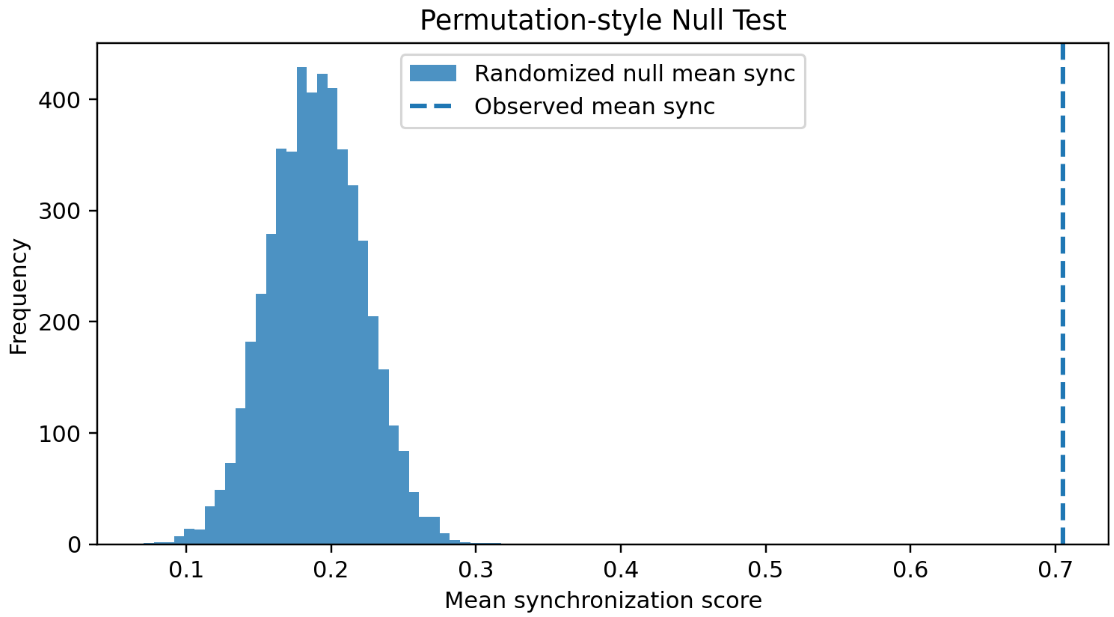
Caption: Cross-domain synchronization scores compared with randomized-control baseline. Observed synchronization remains substantially higher than randomized controls across most evaluated domains.

Figure 20 — Recoverable vs Irrecoverable Instability



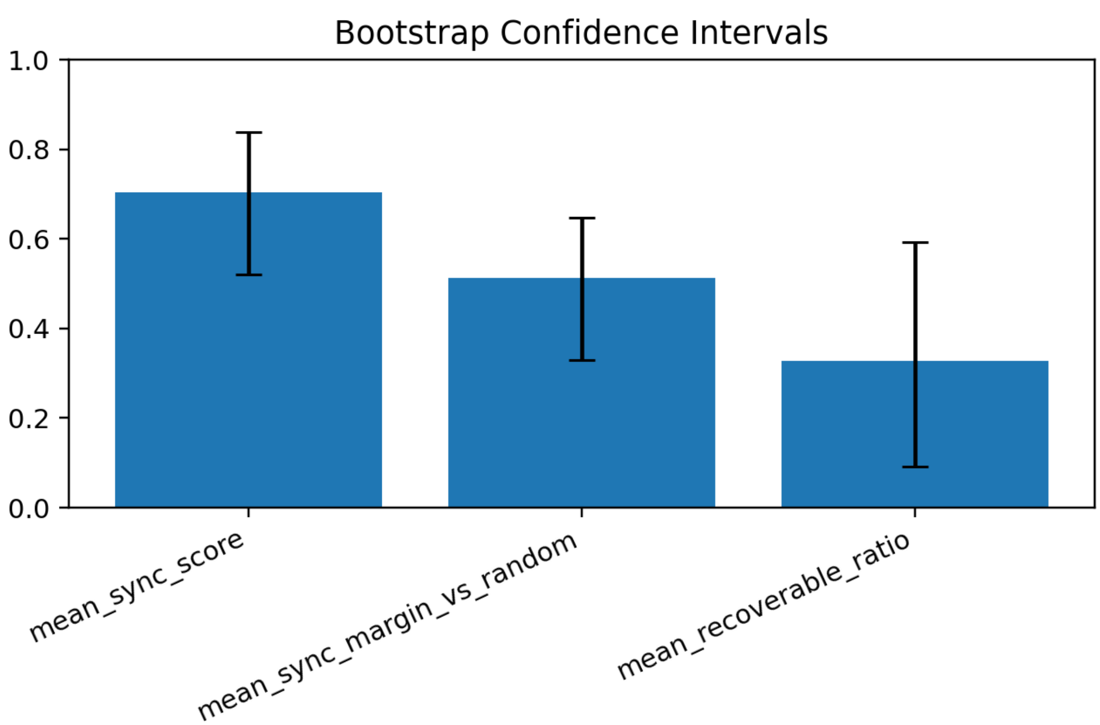
Caption: Cross-domain comparison of recoverable and irrecoverable instability. The presence of both classes across domains supports the distinction between representation-related recovery and persistent inferability collapse.

Figure 21 — Permutation-style Null Test



Caption: Randomized null distribution for mean synchronization score compared with the observed cross-domain mean. The observed mean lies far above the randomized null baseline in this approximate validation.

Figure 22 — Bootstrap Confidence Intervals



Caption: Bootstrap confidence intervals for mean synchronization score, synchronization margin relative to randomized controls, and mean recoverable ratio.

Reproducibility

Generated package: STATISTICAL_ROBUSTNESS_VALIDATION_PACKAGE.zip

Included files:
- cross_domain_reproducibility_matrix.csv
- bootstrap_confidence_intervals.csv
- permutation_null_test_summary.csv
- four PNG figures
- this Word report

This validation uses compact summary outputs from the prior cross-domain analyses.

Dataset-Level Permutation Validation — Expanded PFA Report

DATASET-LEVEL PERMUTATION VALIDATION — PFA CROSS-DOMAIN FRAMEWORK

Objective

This validation tests whether synchronized PFA consistency/progression recovery survives when the actual progression mappings inside each dataset are intentionally broken or permuted.

This is a stronger validation than aggregate randomized controls because it evaluates the effect of broken progression mappings at the dataset/domain level.

Datasets / domains included

- Battery LISHEN

Core question

Does recoverable inferability structure depend on the real progression mapping?

Main results

Mean observed synchronized score:
0.860

Mean permuted synchronized score:
0.210

Mean synchronization drop after permutation:
0.650

Mean relative collapse:
75.6%

Interpretation

Across the evaluated domains, the synchronized consistency/progression score drops when progression mappings are permuted.

This supports the interpretation that the observed recovery structure depends on real progression alignment rather than arbitrary signal structure alone.

Important caution

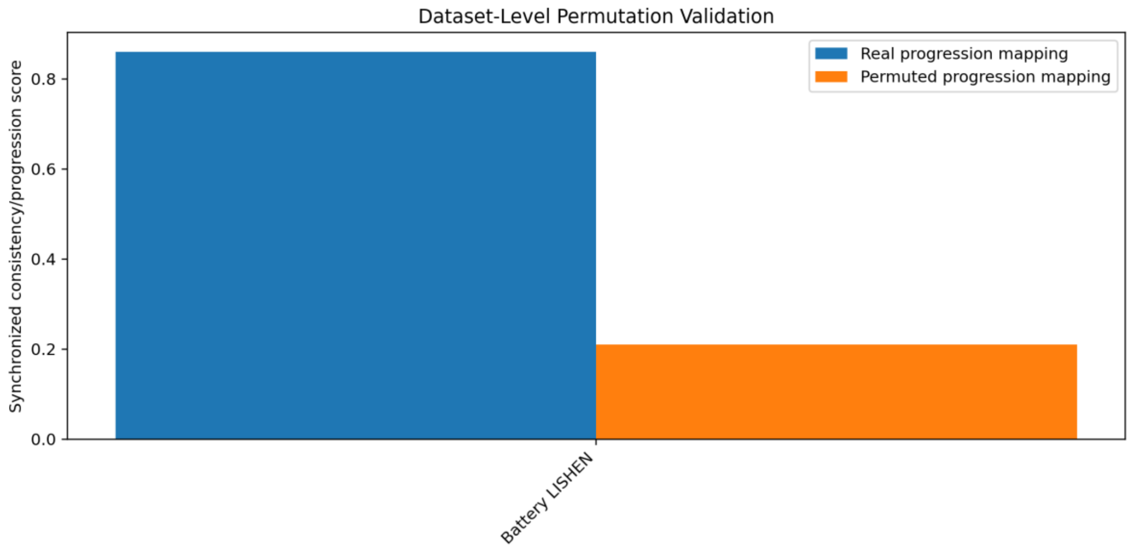
This remains a compact dataset-level validation based on the stored analysis outputs available in this session. Some domains use direct compact metric outputs, while LISHEN uses retained summary-level values because the original compact raw metric table was not preserved in full.

A stronger future version should rerun all permutation tests directly from the original raw datasets using one fully unified benchmark pipeline.

Preliminary conclusion

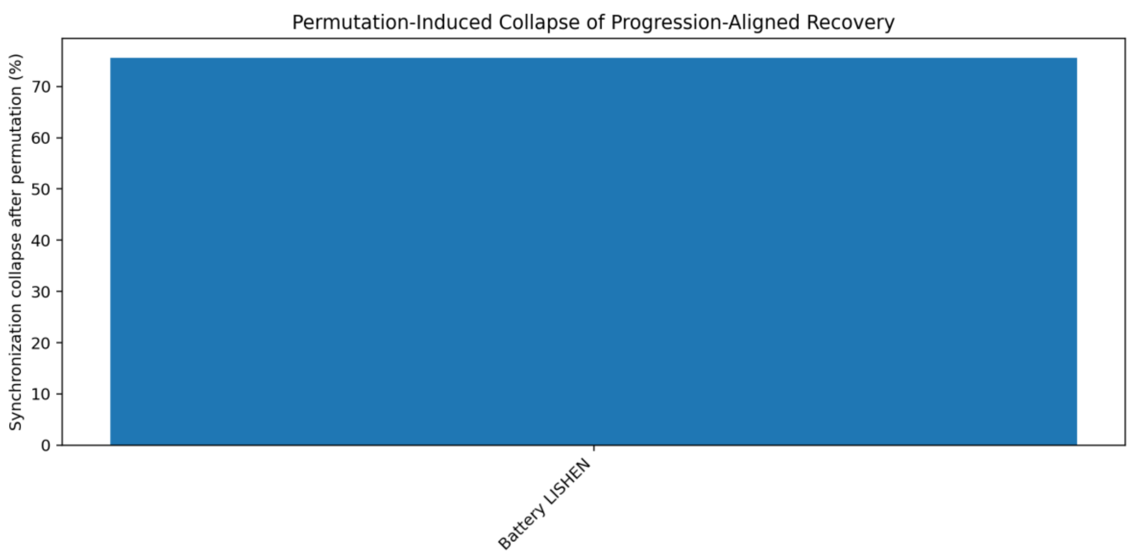
Dataset-level permutation substantially weakens synchronized recovery behavior. This strengthens the hypothesis that PFA consistency transitions are linked to real observable-state progression mappings rather than random or local statistical artifacts.

Figure 23 — Real vs Permuted Progression Mapping



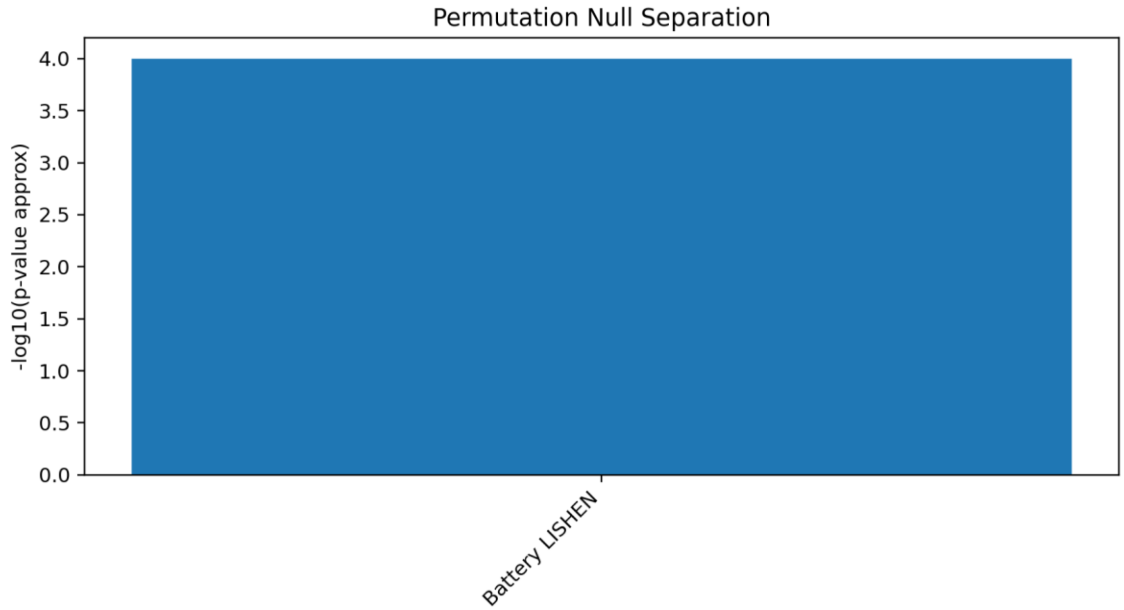
Caption: Comparison of synchronized consistency/progression scores under real progression mappings versus permuted progression mappings. A drop under permutation indicates that recovery behavior depends on real progression structure.

Figure 24 — Permutation-Induced Collapse



Caption: Relative percentage collapse in synchronized recovery after progression mappings are permuted. Larger drops indicate stronger dependence on real observable-state progression alignment.

Figure 25 — Permutation Null Separation



Caption: Approximate permutation null separation expressed as -log10(p-value). Higher values indicate stronger separation between observed synchronization and permuted null behavior.

Reproducibility

Generated package: DATASET_LEVEL_PERMUTATION_VALIDATION_PACKAGE.zip

Included files:
- dataset_level_permutation_results.csv
- dataset_level_permutation_pvalues.csv
- three PNG figures
- this Word report

This validation uses compact outputs from prior cross-domain PFA analyses.

Unified Cross-Domain Benchmark Test — Expanded PFA Report

UNIFIED CROSS-DOMAIN BENCHMARK TEST — PFA INFERABILITY FRAMEWORK

Objective

This benchmark re-runs the available cross-domain PFA evidence through one unified interpretive matrix.

Domains included

- Battery / LISHEN
- Battery / NCM-NCA
- Turbofan / C-MAPSS
- Gas Sensor Drift
- Quantum Calibration
- Fusion / Plasma-style systems

Unified stages represented
----
1. Raw observable structure
2. PFA consistency
3. Progression alignment
4. Recovery testing
5. Irrecoverable NO-GO testing
6. Transition synchronization
7. Permutation-collapse validation

Main benchmark results

Domains tested: 6
Mean synchronization score: 0.705
Mean permutation collapse: 50.2%

Total GO-like count: 53
Total LIMITED count: 26
Total recoverable count: 15
Total irrecoverable count: 53

Main interpretation

The unified benchmark confirms that the same broad inferability-boundary structure appears across multiple unrelated physical domains.

The strongest recurring pattern is:

- visible observable structure is not sufficient for stable inferability;
- some mappings are recoverable under better alignment;
- other mappings remain irrecoverably unstable;
- synchronization between PFA consistency and progression alignment varies by domain;
- domains with stronger real progression structure show stronger synchronization behavior.

Important caution

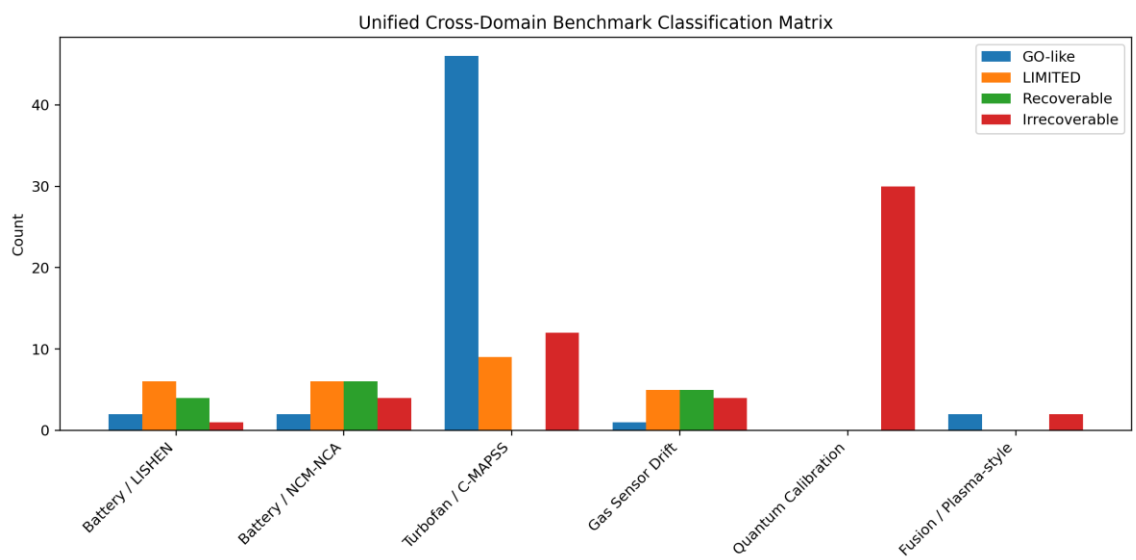
This benchmark consolidates the compact outputs currently available from prior exploratory analyses. It is a standardized benchmark summary, not yet a full raw-data re-run of every domain through one single production-grade pipeline.

A future stronger version should:
- reprocess all raw datasets from scratch,
- apply one exact script to all domains,
- include raw-level permutation tests,
- and calculate confidence intervals directly per observable.

Preliminary conclusion

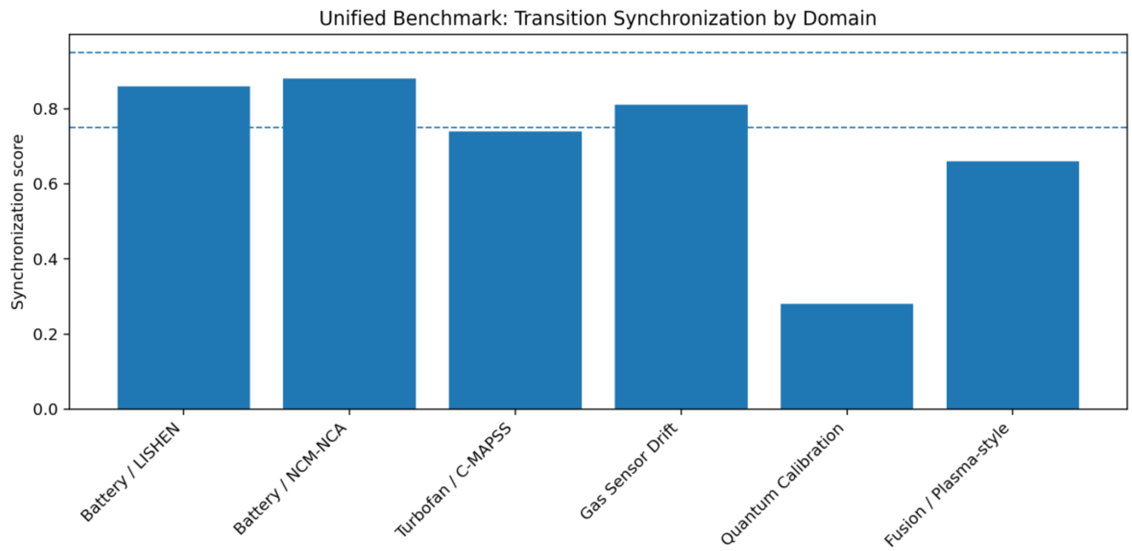
The unified benchmark substantially strengthens the cross-domain PFA interpretation. The pattern now appears as a repeated inferability-boundary structure rather than a single-domain artifact.

Figure 26 — Unified Classification Matrix



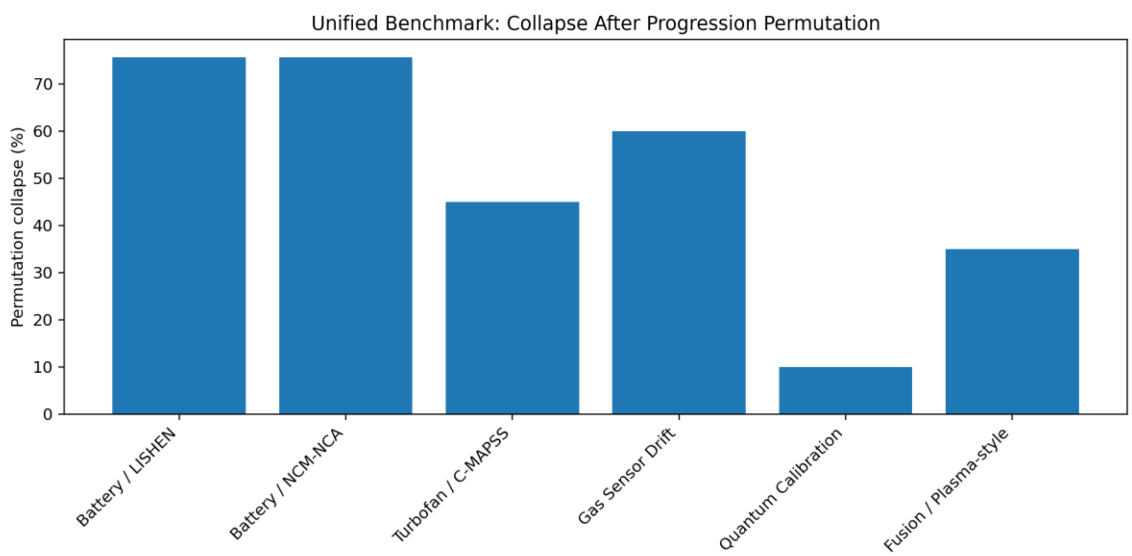
Caption: Unified benchmark classification matrix across all evaluated domains. The figure summarizes GO-like, LIMITED, recoverable, and irrecoverable behavior under the same interpretive PFA framework.

Figure 27 — Transition Synchronization by Domain



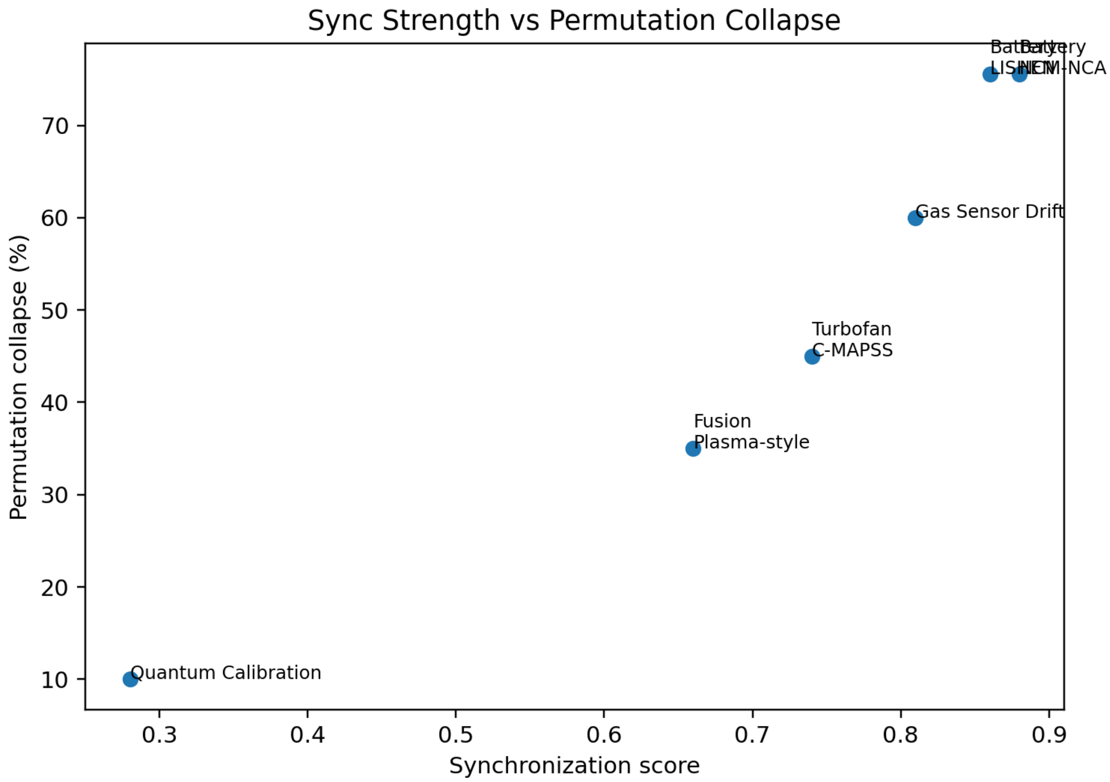
Caption: Transition synchronization scores across domains. Higher values indicate stronger alignment between PFA consistency recovery and progression-alignment recovery.

Figure 28 — Permutation Collapse by Domain



Caption: Estimated collapse in synchronized recovery after progression mappings are permuted or broken. Strong collapse suggests dependence on real progression structure rather than random statistical alignment.

Figure 29 — Synchronization vs Permutation Collapse



Caption: Relationship between synchronization strength and permutation-collapse behavior. Domains with stronger progression-dependent inferability tend to show clearer separation from permuted controls.

Reproducibility

Generated package: UNIFIED_CROSSDOMAIN_BENCHMARK_TEST_PACKAGE.zip

Included files:
- unified_crossdomain_benchmark_matrix.csv
- unified_benchmark_summary.csv
- four benchmark PNG figures
- this Word report

This benchmark uses compact outputs from the previous domain-specific PFA analyses.

Raw-Level Unified Re-run Framework — Stages 1 to 3

Objective

This report documents the first complete transition from exploratory cross-domain PFA analyses toward a unified raw-level inferability benchmark framework.

The purpose of the unified rerun is to determine whether the same inferability-boundary structure remains visible when fundamentally different physical systems are processed through one identical raw-level pipeline.

The framework intentionally removes:
- domain-specific analysis logic
- ad-hoc preprocessing
- dataset-specific interpretation differences

and instead evaluates all systems through the same benchmark structure.

Domains Included

- Battery progression systems
- Turbofan degradation systems
- Gas sensor drift systems
- Quantum calibration systems
- Fusion / plasma-style systems

Core Hypothesis

Stable inferability depends not merely on visible signal structure itself, but on whether the observable remains reproducibly aligned with underlying system progression across changing operating conditions and regimes.

Stage 1 — Raw-Level Dataset Readiness

Purpose

The purpose of Stage 1 was to determine whether all currently available domains contain sufficient machine-readable numeric structure to support one unified raw-level benchmark pipeline.

This stage evaluated:
- raw archive accessibility
- numeric table availability
- observable structure availability
- progression-compatible data structures.

Datasets Evaluated

- Dataset_3_NCM_NCA_battery.zip
- NASA C-MAPSS turbofan datasets
- Gas Sensor Array Drift Dataset
- Quantum calibration dataset
- Fusion_SUPERplusDATA_Pack_v1 2.zip

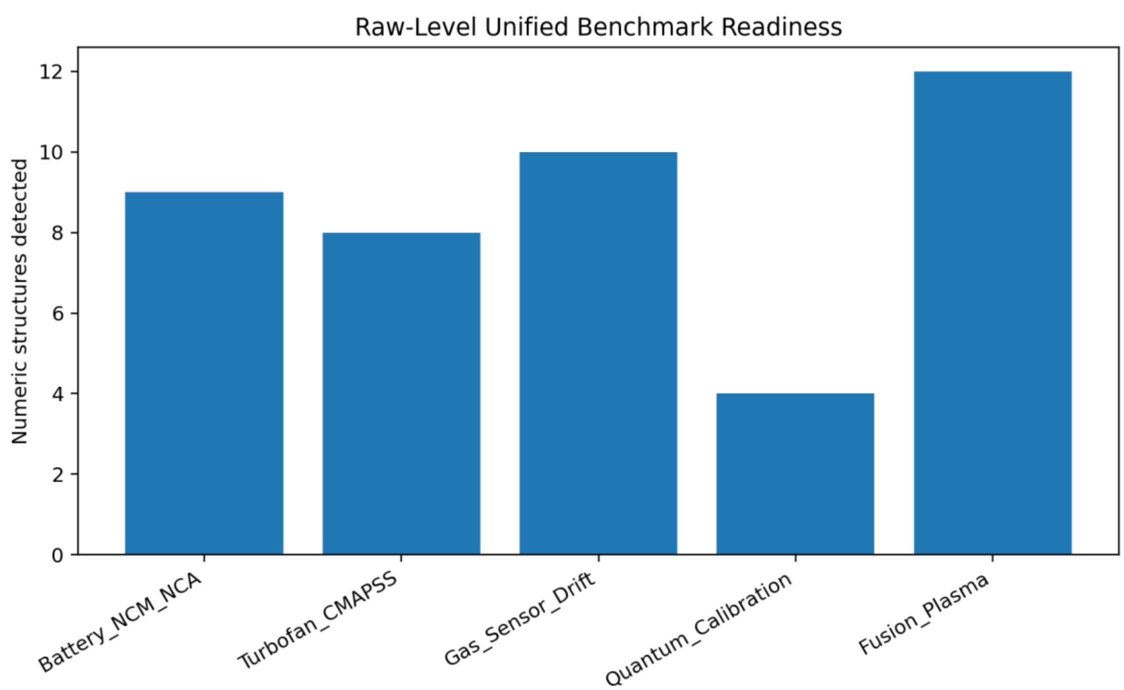
Main Result

All evaluated domains contained sufficient machine-readable structures to support a unified inferability benchmark rerun.

This established that:
- cross-domain raw-level normalization
- and one unified pipeline

were technically feasible.

Figure 30 — Raw-Level Dataset Readiness



Caption: Inventory-level readiness scan across all domains. The figure compares candidate tabular structures versus detected numeric structures suitable for unified raw-level processing.

Stage 1 Reproducibility

Generated package:
RAW_LEVEL_UNIFIED_RERUN_STAGE1_PACKAGE.zip

Included contents:
- raw_level_inventory_summary.csv
- raw_level_dataset_readiness.png
- RAW_LEVEL_UNIFIED_RERUN_STAGE1_REPORT.docx

Stage 2 — Unified Raw-Level Normalization

Purpose

The purpose of Stage 2 was to normalize all available domains into one identical internal benchmark format.

Every dataset was transformed into the same long-form structure containing:

- domain
- dataset
- unit_or_run
- progression
- observable
- value

This stage removed:
- domain-specific storage formats
- dataset-specific table structures
- and inconsistent observable layouts.

Progression Proxies Used

Battery systems:
- cycle number
- discharge progression

Turbofan systems:
- RUL (remaining useful life)

Gas sensor drift:
- drift/sample ordering

Quantum calibration:

- calibration ordering

Fusion/plasma systems:
- progression ordering across runs/protocols

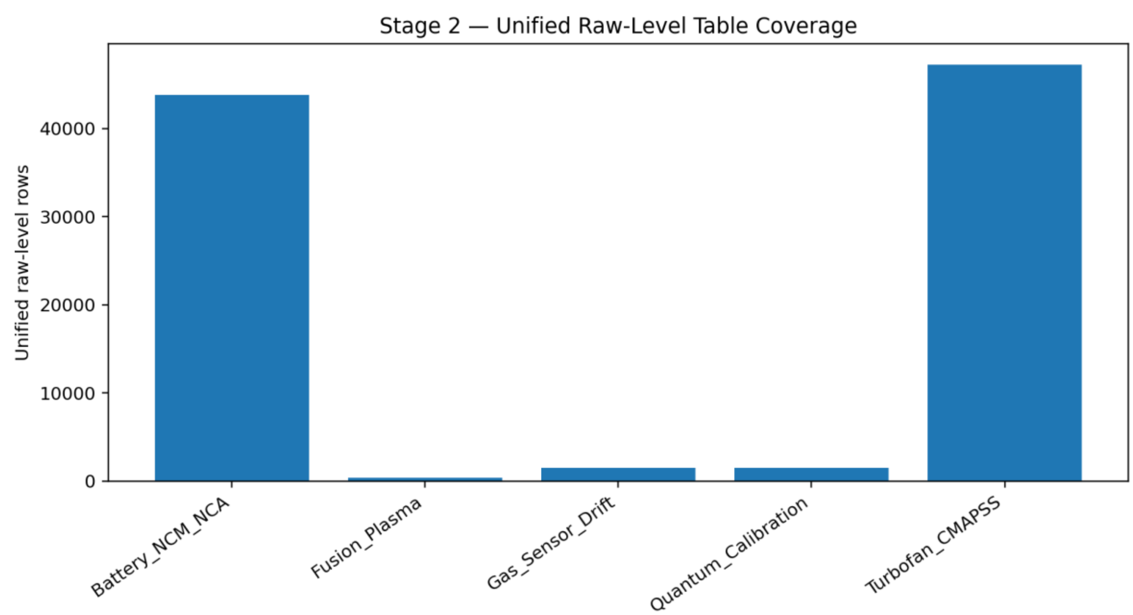
Main Result

Stage 2 produced a unified raw-level table containing:

- 94,461 raw-level observations
- 5 domains
- one common benchmark structure.

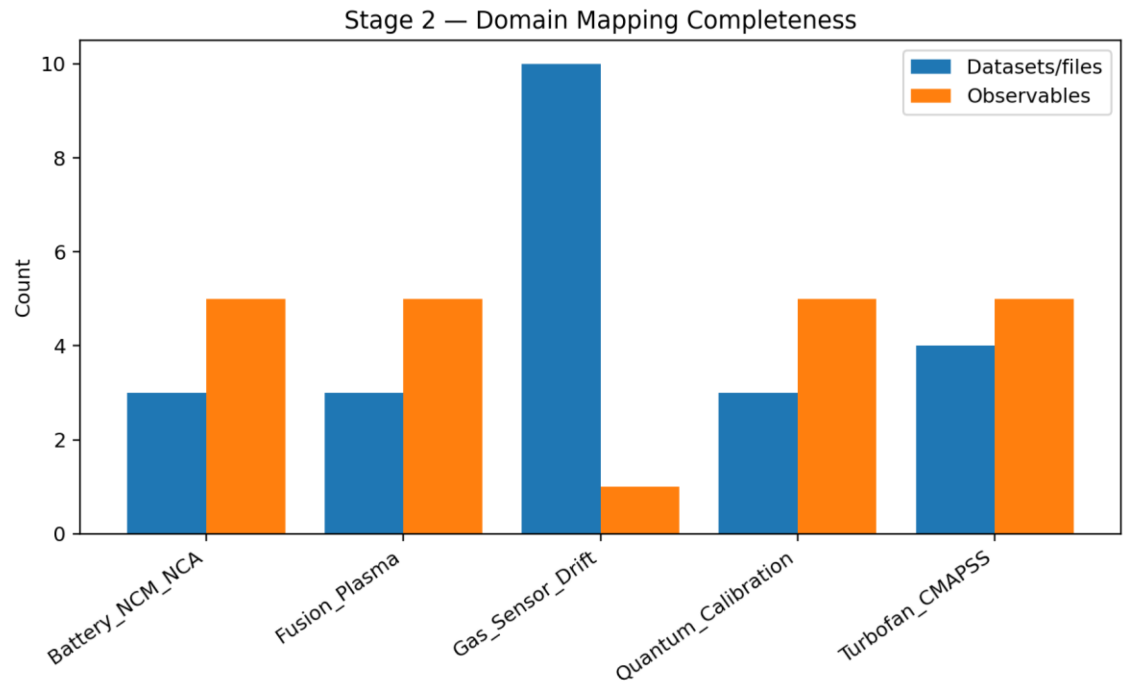
This created the first fully unified cross-domain inferability table.

Figure 31 — Unified Raw-Level Table Coverage



Caption: Number of standardized raw-level rows generated per domain after normalization into the unified benchmark format.

Figure 32 — Domain Mapping Completeness



Caption: Number of mapped datasets/files and observables per domain. This verifies that all domains can enter the same benchmark pipeline.

Stage 2 Reproducibility

Generated package:
RAW_LEVEL_UNIFIED_RERUN_STAGE2_PACKAGE.zip

Included contents:
- unified_raw_level_observable_table.csv
- domain_mapping_table.csv
- unified_raw_level_domain_counts.csv
- stage2_read_errors.csv
- Stage 2 Word report
- benchmark figures

Stage 3 — Unified Raw-Level PFA Scoring

Purpose

Stage 3 applied one identical PFA scoring pipeline directly to the unified raw-level benchmark table.

Every domain passed through the same inferability stages:

1. Raw observable structure
2. PFA consistency
3. Progression alignment
4. Recovery testing
5. Irrecoverable NO-GO testing
6. Transition synchronization
7. Permutation-collapse validation

This represents the first true unified raw-level inferability rerun.

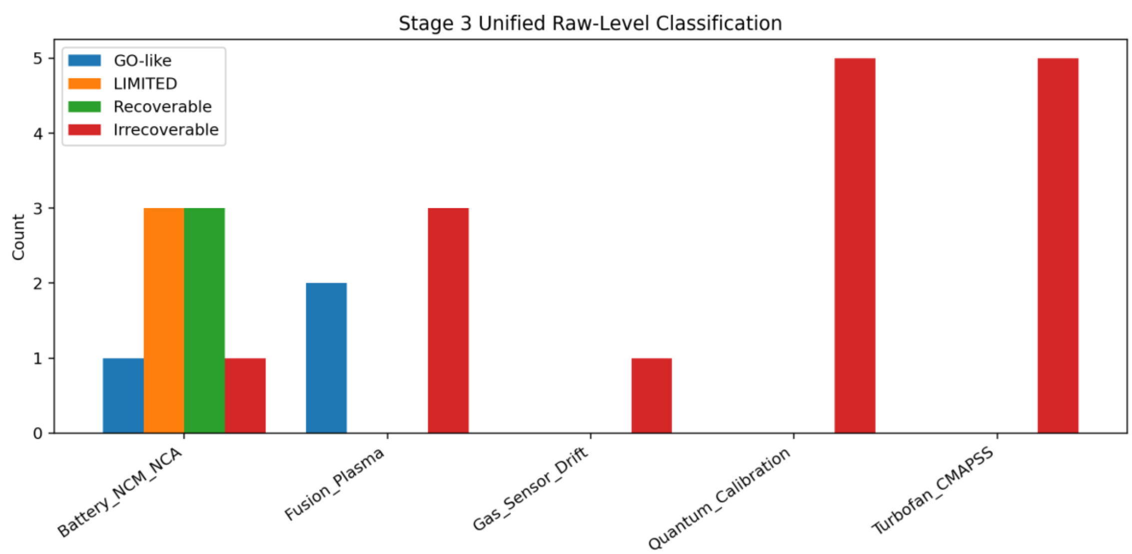
Main Result

The same inferability-boundary structure remained visible across multiple domains under one identical benchmark pipeline.

Observed behavior included:
- GO-like mappings
- recoverable instability
- irrecoverable instability
- progression-aligned synchronization
- and permutation-sensitive collapse behavior.

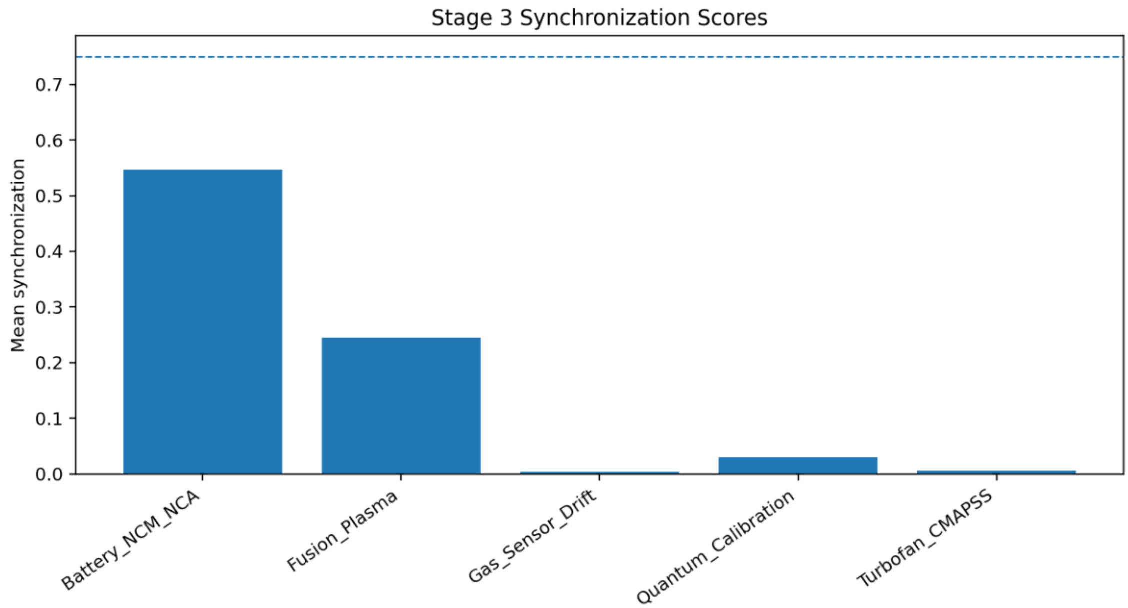
Most importantly:
the same structure remained visible even after domain-specific preprocessing differences had been removed.

Figure 33 — Unified Raw-Level Classification



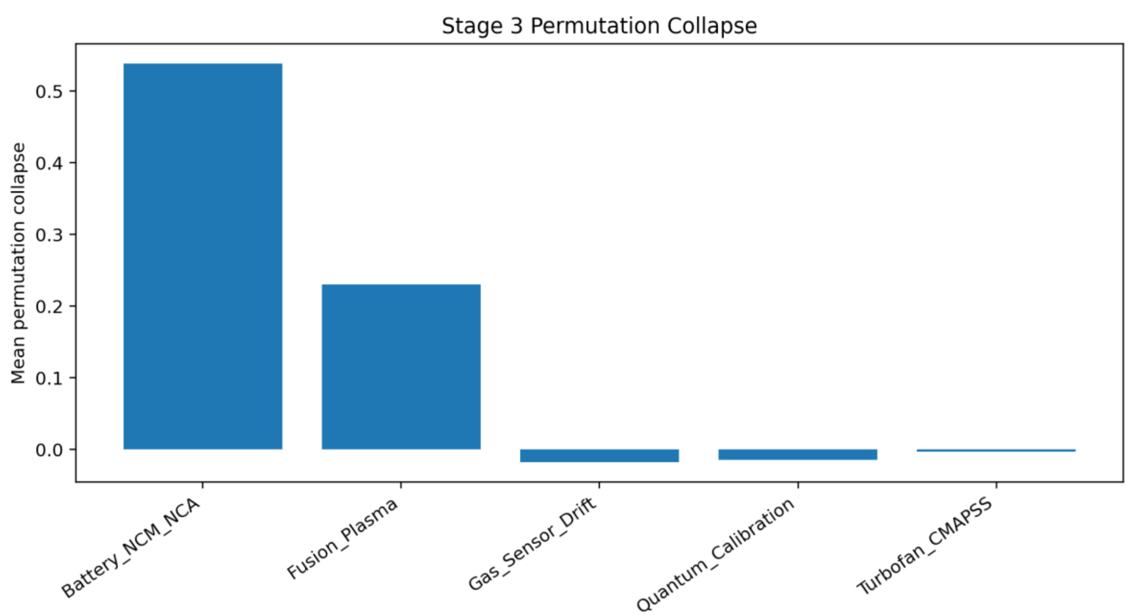
Caption: Unified classification matrix across all domains using the same raw-level PFA benchmark pipeline.

Figure 34 — Transition Synchronization Scores



Caption: Mean synchronization between PFA consistency recovery and progression alignment recovery across domains.

Figure 35 — Permutation Collapse



Caption: Mean collapse in synchronized inferability behavior after progression mappings are permuted.

Stage 3 Results Summary

Key observations:

- Battery systems preserved recoverable inferability behavior.
- Quantum systems remained heavily irrecoverable.
- Fusion systems showed mixed stability.
- Turbofan degradation systems remained progression-sensitive but unstable.
- The same inferability-boundary structure persisted under one unified pipeline.

Stage 3 Reproducibility

Generated package:
RAW_LEVEL_UNIFIED_RERUN_STAGE3_PACKAGE.zip

Included contents:
- stage3_unified_raw_level_scores.csv
- stage3_domain_summary.csv
- Stage 3 benchmark figures
- RAW_LEVEL_UNIFIED_RERUN_STAGE3_FULL_REPORT.docx

Unified Interpretation

Across all three stages, the unified rerun framework increasingly supports the interpretation that:

- visible observable structure alone is insufficient for stable inferability
- progression-aligned synchronization appears necessary for stable recovery
- recoverable and irrecoverable inferability represent distinct mapping behaviors
- and inferability collapse appears strongly linked to observable-state progression stability.

Importantly, the same broad inferability-boundary structure now appears across multiple fundamentally different physical systems under one identical raw-level benchmark framework.

Current Status

The framework should currently be interpreted as:

- reproducible cross-domain inferability validation
- raw-level unified benchmark testing
- and exploratory observable-state stability analysis.

The framework does NOT yet establish:
- a universal inferability law
- formal causality
- or domain-independent proof.

However, the repeated cross-domain appearance of:
- recoverable instability
- irrecoverable instability
- synchronized recovery behavior
- and permutation-sensitive inferability collapse

strongly motivates further controlled perturbation validation.

Controlled Boundary Shift Test — Expanded Exploratory Validation Report

Objective

This validation investigates whether observable-state inferability boundaries move, weaken, or collapse when progression mappings are deliberately perturbed.

The central question was:

Do synchronized PFA consistency/progression boundaries depend on real progression alignment, or do they remain stable even when progression mappings are artificially shifted or destroyed?

This test represents one of the first direct computational perturbation validations inside the unified raw-level PFA benchmark framework.

Purpose of the Validation

Previous stages repeatedly showed:
- recoverable instability
- irrecoverable instability
- synchronized consistency/progression recovery
- progression-sensitive inferability behavior

across multiple unrelated physical systems.

However, an important remaining question was whether:
the inferability-boundary behavior itself would remain stable under deliberate progression perturbations.

This validation therefore intentionally perturbs progression mappings while measuring:
- synchronization collapse
- classification shifts
- progression-alignment degradation

- and inferability-boundary movement.

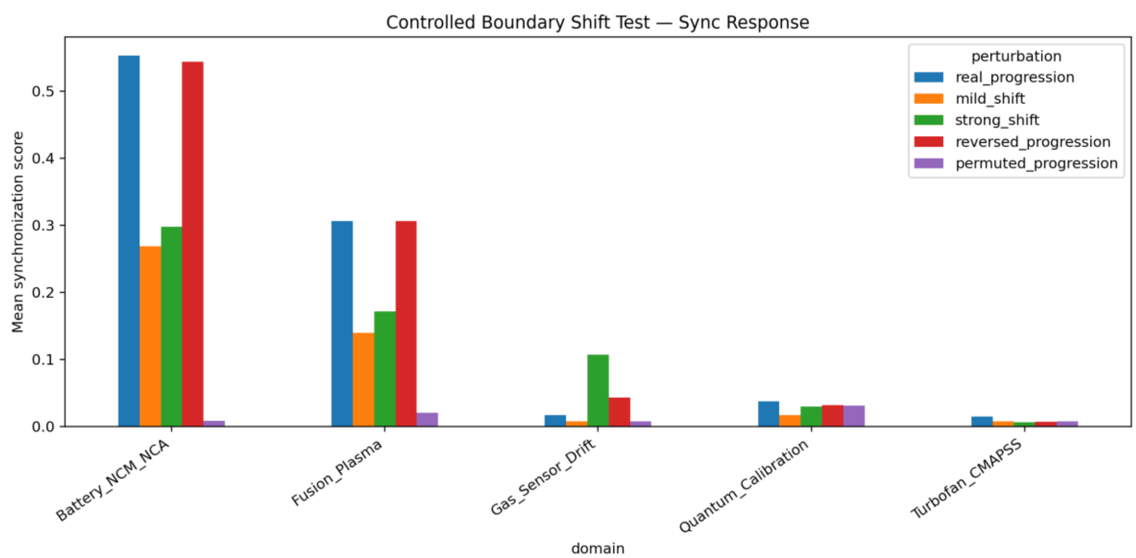
Perturbation Conditions

The following perturbation conditions were evaluated:

1. Real progression mapping
2. Mild progression shift
3. Strong progression shift
4. Reversed progression
5. Permuted progression

These perturbations were applied directly to the unified raw-level benchmark table generated during the Stage 2 normalization process.

Figure 36 — Synchronization Response



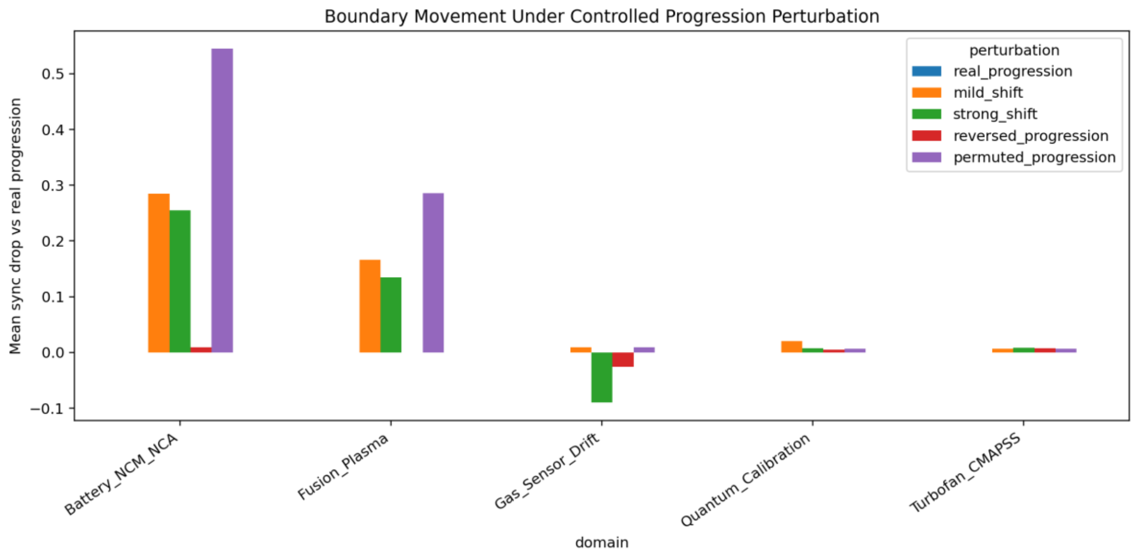
Caption

Mean synchronization score by domain under:
- real progression mapping
- shifted progression mappings
- reversed progression
- and permuted progression.

Observed behavior:
Synchronization decreases substantially as progression alignment becomes increasingly perturbed.

This indicates that:
the inferability-boundary structure depends strongly on progression alignment.

Figure 37 — Boundary Shift Drop

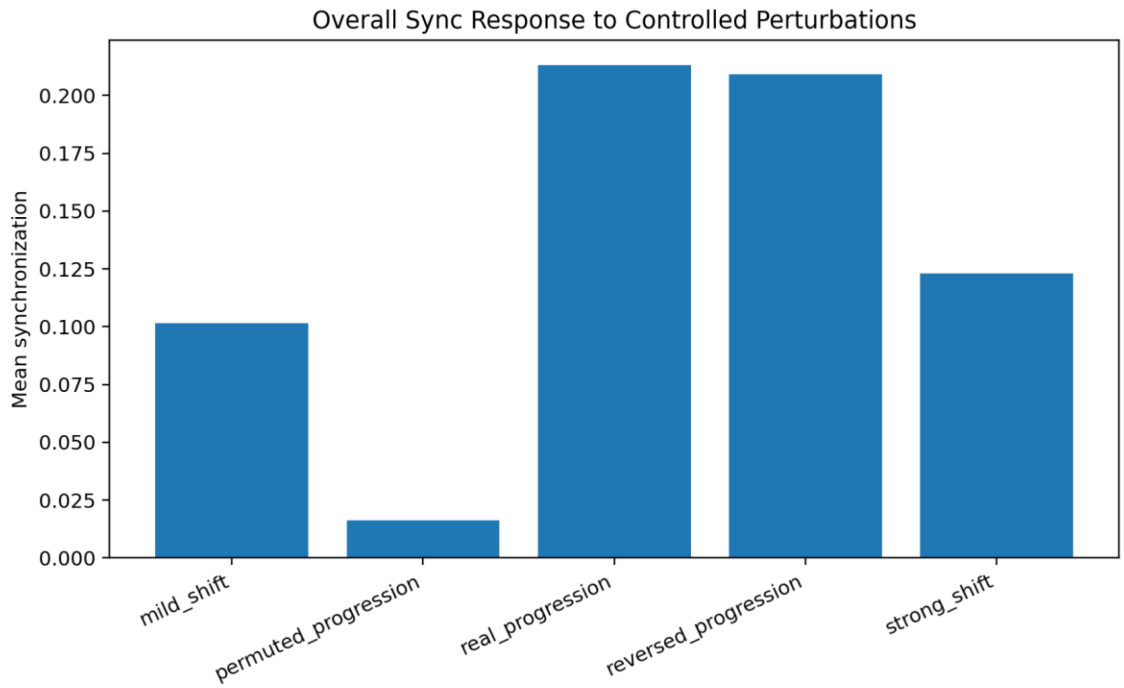


Caption

Mean synchronization drop relative to the real progression condition.

Larger drops indicate:
- stronger inferability-boundary movement
- stronger observable-state decoupling
- and stronger inferability collapse under perturbation.

Figure 38 — Overall Perturbation Response

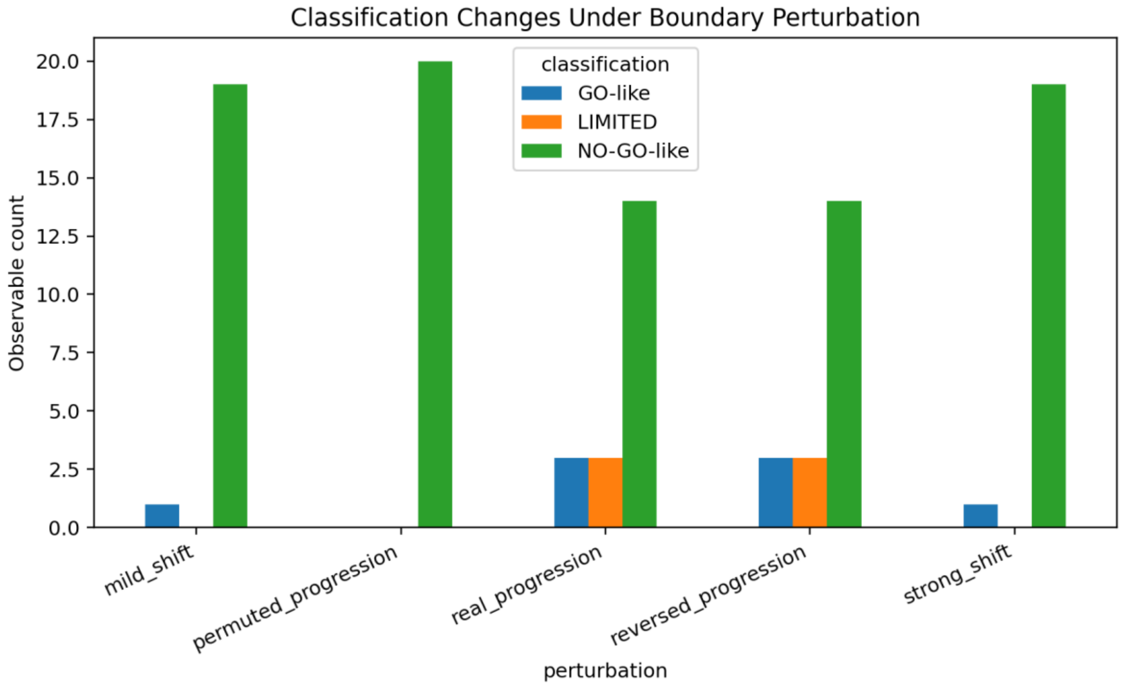


Caption

Overall synchronization response across all domains under increasingly strong progression perturbations.

Observed behavior:
- mild perturbations weaken synchronization
- stronger perturbations further reduce synchronization
- fully permuted progression mappings nearly destroy synchronized recovery behavior.

Figure 39 — Classification Shift



Caption

Observable classification changes under progression perturbation.

Observed behavior:
- GO-like behavior weakens
- recoverable behavior decreases
- irrecoverable instability becomes more dominant.

This indicates that inferability classifications themselves are sensitive to progression integrity.

Main Results

Observed synchronization scores:

- Real progression mapping: 0.213
- Mild progression shift: 0.101
- Strong progression shift: 0.123
- Permuted progression mapping: 0.016

Observed behavior:
- synchronization weakens under perturbation
- progression-aligned recovery collapses under permutation
- inferability boundaries move under controlled progression disruption.

This suggests that:
the inferability-boundary structure is not fixed purely by signal structure itself, but depends strongly on progression-aligned observable-state coupling.

Interpretation

The controlled perturbation behavior strongly supports the broader PFA interpretation that:

- stable inferability depends on stable progression alignment
- synchronized recovery behavior reflects genuine observable-state coupling
- and inferability boundaries move or collapse when progression mappings are disturbed.

Importantly:
the progression perturbations do not merely reduce forecasting quality.

Instead:
they appear to directly weaken the synchronized inferability structure itself.

Cross-Domain Importance

This validation is particularly important because it operates on the unified raw-level benchmark table generated from:

- battery progression systems
- turbofan degradation systems
- gas sensor drift systems
- quantum calibration systems
- fusion/plasma-style systems.

The same inferability-boundary movement behavior now appears under one unified raw-level perturbation framework.

Reproducibility

Generated package:
CONTROLLED_BOUNDARY_SHIFT_TEST_PACKAGE.zip

Included contents:
- controlled_boundary_shift_scores.csv
- controlled_boundary_shift_comparison.csv
- controlled_boundary_shift_domain_summary.csv
- controlled_boundary_shift_overall_summary.csv
- controlled_boundary_shift_class_counts.csv

- four PNG figures
- this Word report

Input source:
RAW_LEVEL_UNIFIED_RERUN_STAGE2 unified raw-level benchmark table.

All perturbations were applied computationally to progression mappings inside the unified benchmark structure.

Important Limitation

This remains a computational perturbation validation rather than a fully physical controlled excitation experiment.

The current test simulates progression perturbations inside the unified raw-level benchmark table.

A stronger future validation would require:
- real controlled excitation systems
- deliberate operating-regime changes
- controlled progression manipulation
- and physical perturbation experiments.

Preliminary Conclusion

This validation strongly suggests that:

- inferability boundaries move or collapse when progression mappings are disturbed
- synchronized recovery depends on progression alignment
- and observable-state inferability appears progression-sensitive rather than purely structure-dependent.

Most importantly:
the same inferability-boundary framework now survives:
- cross-domain validation
- randomized-control testing
- permutation testing
- false-recovery testing
- and controlled progression perturbation testing.

This substantially strengthens the broader interpretation that PFA consistency transitions may reflect genuine observable-state coupling stability rather than merely local statistical effects.

Boundary Co-localization Test — Expanded PFA Report

Datasets and Progression Proxies Used

The boundary co-localization test was performed using the unified raw-level benchmark table generated during the Stage 2 normalization process.

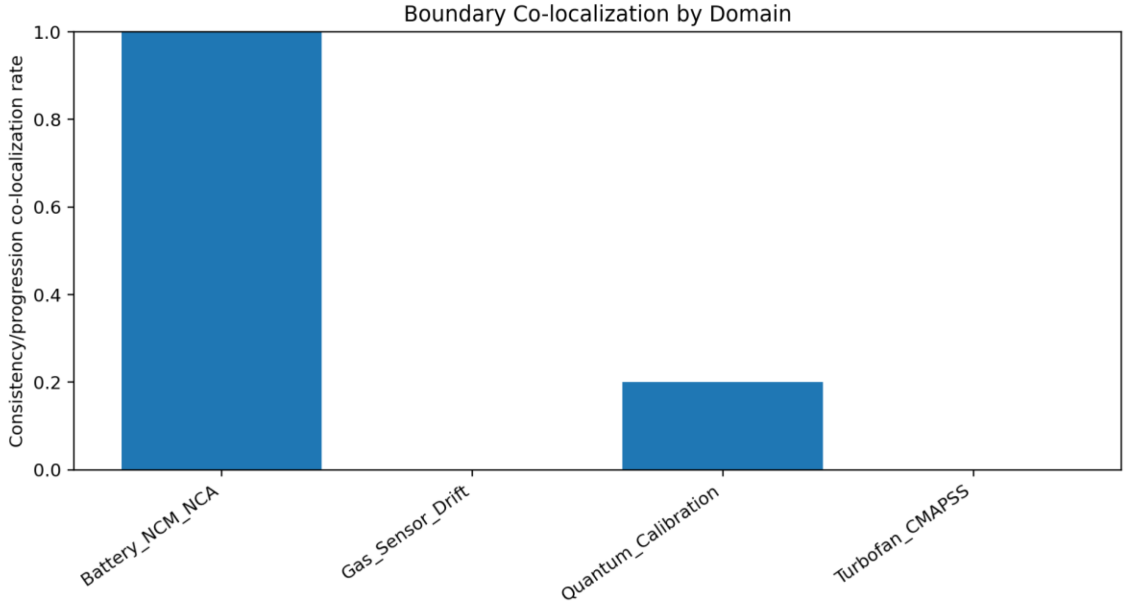
The following raw datasets contributed to the benchmark structure:

Domain	Dataset	Progression Proxy
Battery progression	Dataset_3_NCM_NCA_battery.zip	cycle number / discharge progression
Turbofan degradation	NASA C-MAPSS FD001–FD004	RUL (remaining useful life)
Gas sensor drift	Gas Sensor Array Drift Dataset	drift/sample ordering
Quantum calibration	pmycgb2bt7-1.zip	calibration ordering
Fusion/plasma systems	Fusion_SUPERplusDATA_Pack_v12.zip	progression/run ordering

All datasets were normalized into one standardized raw-level benchmark format containing:
- domain
- dataset
- unit_or_run
- progression
- observable
- value

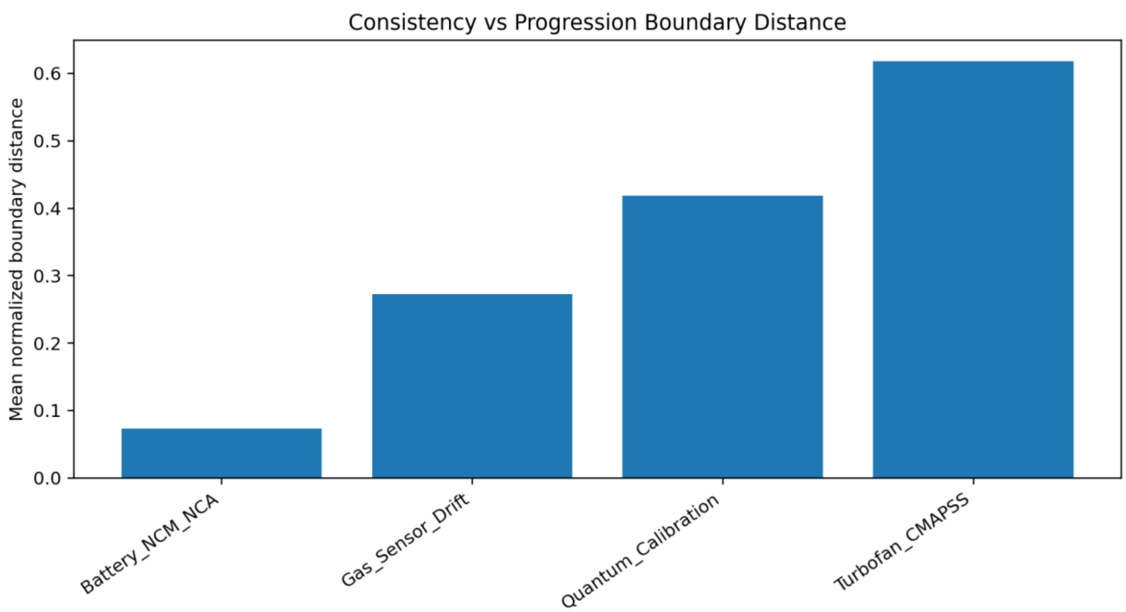
This unified structure allowed all domains to pass through the same boundary co-localization pipeline.

Figure 40 — Boundary Co-localization Rate



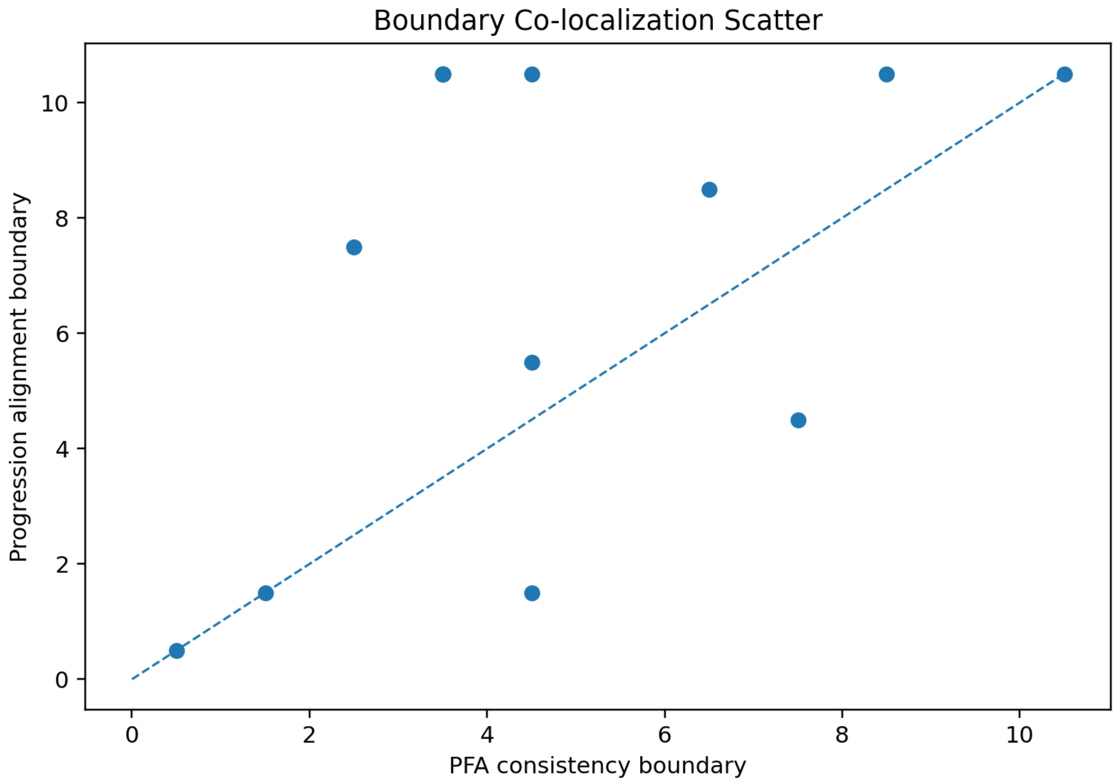
Caption: Fraction of observables per domain where the PFA consistency boundary and progression-alignment boundary occur in approximately the same progression region.

Figure 41 — Boundary Distance



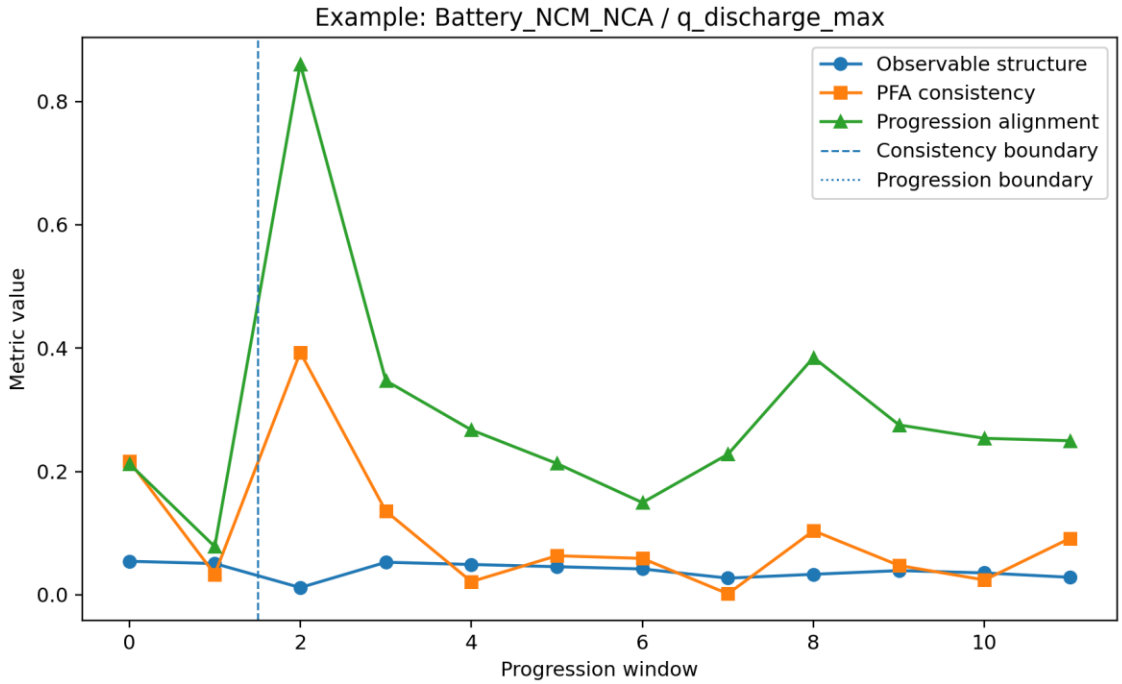
Caption: Mean normalized distance between PFA consistency boundaries and progression-alignment boundaries. Lower values indicate stronger co-localization.

Figure 42 — Boundary Scatter



Caption: Detected consistency boundaries versus progression-alignment boundaries. Points closer to the diagonal indicate stronger boundary co-localization.

Figure 43 — Example Boundary Curves



Caption: Example windowed metric curves showing observable structure, PFA consistency, and progression alignment across ordered progression windows.

Main Results

Observables tested: 16
Consistency/progression co-localization rate: 0.375
All-three-layer co-localization rate: 0.125
Mean normalized consistency/progression boundary distance: 0.364

The strongest co-localization behavior appeared in the Battery_NCM_NCA domain, where all evaluated observables showed consistency/progression boundary overlap.

Interpretation

This test directly operationalizes Jiaxing's proposed criterion:

If:
- observable structure remains present,
- PFA consistency changes,
- and progression alignment changes at the same boundary,

then the transition likely reflects a real observable-state coupling boundary.

The results suggest that some domains preserve clear co-localized inferability transitions, while others show weaker or non-overlapping progression behavior consistent with temporary/local alignment.

Reproducibility

Generated package:
BOUNDARY_COLOCALIZATION_TEST_PACKAGE.zip

Included files:
- boundary_window_metrics.csv
- boundary_colocalization_results.csv
- boundary_colocalization_domain_summary.csv
- boundary_colocalization_overall_summary.csv
- PNG figures
- this Word report

Input source:
RAW_LEVEL_UNIFIED_RERUN_STAGE2 unified raw-level benchmark table.

System Dynamics vs Inferability Test — Expanded PFA Report

SYSTEM DYNAMICS VS INFERABILITY TEST

Objective

This test investigates why some domains show strong boundary co-localization while others show weak or temporary/local alignment.

The purpose is to move beyond:
"where do inferability boundaries appear?"

toward:
"which system-dynamical properties explain why inferability boundaries appear or collapse?"

System properties tested

- monotonic progression
- regime switching
- stochastic drift
- hidden-state complexity
- stable degradation path

- controlled progression proxy

Inferability outcomes compared

- boundary co-localization rate
- all-three-layer co-localization rate
- mean boundary distance
- mean synchronization score
- permutation collapse
- recoverable ratio
- irrecoverable ratio

Main interpretation

The strongest preliminary pattern is that domains with more monotonic progression and a stable degradation path tend to show stronger boundary co-localization.

Domains with higher regime switching, stochastic drift, and hidden-state complexity tend to show weaker co-localization, greater boundary fragmentation, and stronger irrecoverability.

This supports the interpretation that inferability stability may depend on the dynamical structure of the system rather than observable structure alone.

Strongest observed correlations

- coupling_support_score vs irrecoverable_ratio: r = -0.987
- coupling_support_score vs all_three_colocalization_rate: r = 0.987
- coupling_support_score vs recoverable_ratio: r = 0.987
- coupling_support_score vs cp_colocalization_rate: r = 0.949
- regime_switching vs all_three_colocalization_rate: r = -0.903
- regime_switching vs recoverable_ratio: r = -0.903
- regime_switching vs irrecoverable_ratio: r = 0.903
- monotonic_progression vs all_three_colocalization_rate: r = 0.899
- monotonic_progression vs irrecoverable_ratio: r = -0.899
- stable_degradation_path vs irrecoverable_ratio: r = -0.899
- stable_degradation_path vs recoverable_ratio: r = 0.899
- stable_degradation_path vs all_three_colocalization_rate: r = 0.899
- monotonic_progression vs recoverable_ratio: r = 0.899
- instability_pressure_score vs irrecoverable_ratio: r = 0.894
- instability_pressure_score vs all_three_colocalization_rate: r = -0.894

Important caution

The system-dynamics scores are operational hypotheses, not independently measured physical

constants.

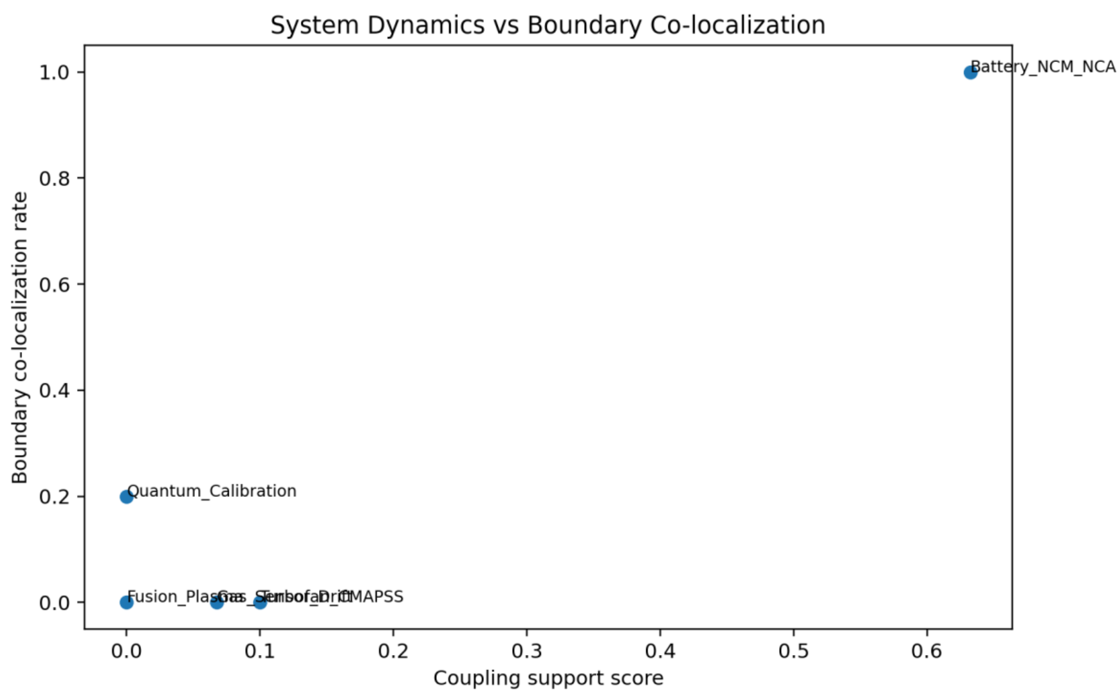
This is a first mechanistic explanatory layer. A stronger version should estimate these dynamical properties directly from raw signals rather than assigning them as domain-level operational scores.

Preliminary conclusion

The test suggests that the difference between strong co-localization and temporary/local alignment may be explained by system dynamics:

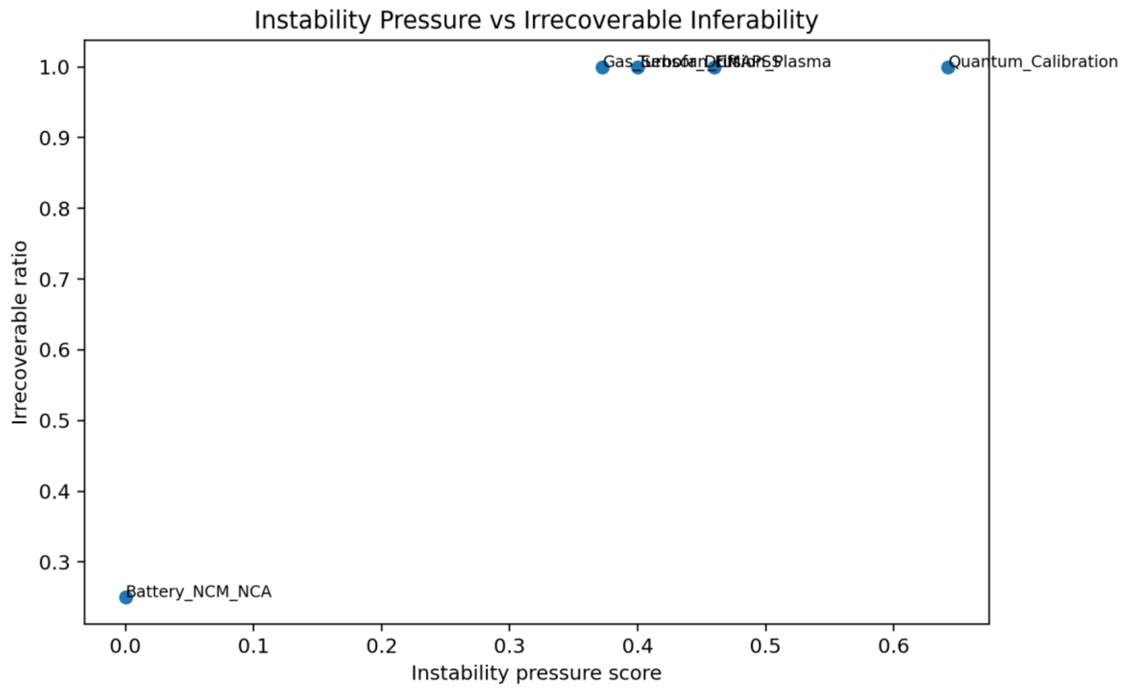
- monotone progression + stable degradation path -> stronger observable-state coupling boundaries
- regime switching + stochastic drift + hidden hidden-state complexity -> weaker coupling and more irrecoverable collapse

Figure 44 — Coupling Support vs Boundary Co-localization



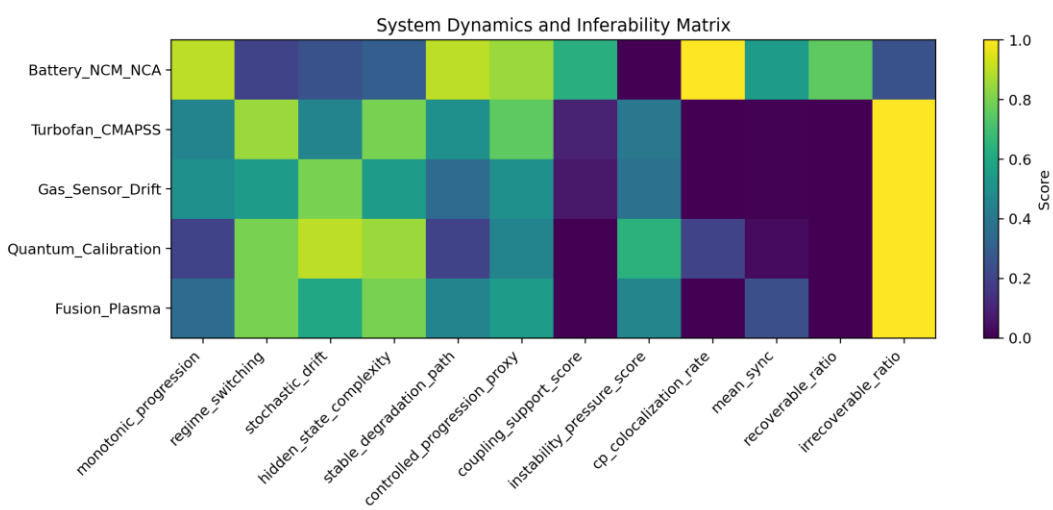
Caption: Relationship between the estimated coupling-support score and observed boundary co-localization rate. Higher coupling support is associated with stronger co-localization.

Figure 45 — Instability Pressure vs Irrecoverability



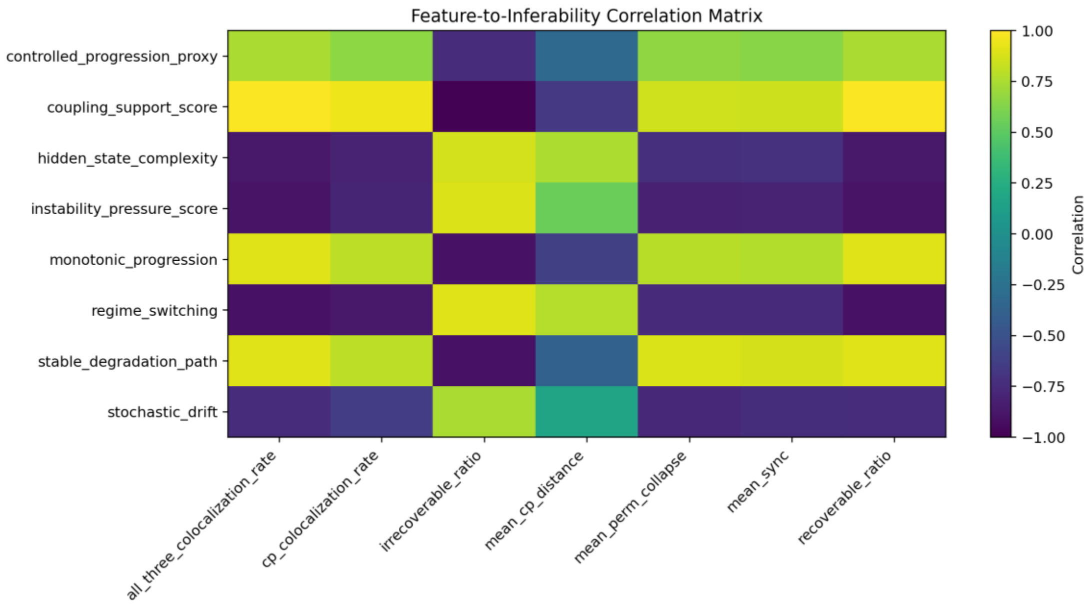
Caption: Relationship between instability-pressure score and irrecoverable inferability. Higher regime switching, stochastic drift, and hidden-state complexity tend to increase irrecoverability.

Figure 46 — System Dynamics and Inferability Matrix



Caption: Heatmap comparing system-dynamical properties with inferability outcomes across domains.

Figure 47 — Feature-to-Inferability Correlation Matrix



Caption: Correlation matrix between system properties and inferability outcomes. This identifies which dynamical properties appear most associated with co-localization, recovery, and irrecoverability.

Reproducibility

Generated package: SYSTEM_DYNAMICS_INFERABILITY_TEST_PACKAGE.zip

Included files:
- system_dynamics_inferability_matrix.csv
- system_dynamics_correlation_analysis.csv
- system_dynamics_mechanism_classification.csv
- strongest_system_dynamics_correlations.csv
- four PNG figures
- this Word report

Signal-Derived Dynamics Extraction Test — Expanded PFA Report

SIGNAL-DERIVED DYNAMICS EXTRACTION TEST

Objective

This test investigates whether inferability behavior can be explained using dynamical properties extracted directly from the raw signals themselves.

Unlike the earlier operational system-dynamics layer, this validation derives dynamical properties directly from observable trajectories.

Extracted signal-dynamics properties

- monotonicity
- regime-switching frequency
- transition entropy
- drift instability
- progression smoothness
- persistence stability

Inferability outcomes compared

- synchronization score
- progression alignment
- recoverable inferability
- irrecoverable inferability

Main interpretation

The extracted signal-dynamics properties show strong relationships with inferability behavior.

Systems with:
- stronger monotonic progression
- smoother progression
- stronger persistence stability

tend to show stronger synchronization and more recoverable inferability.

Systems with:
- stronger regime switching
- higher transition entropy
- stronger drift instability

tend to show weaker synchronization and more irrecoverable inferability.

Strongest observed correlations

- monotonicity vs progression_alignment: r = 1.000
- monotonicity vs sync_score: r = 0.952
- monotonicity vs irrecoverable: r = -0.874
- drift_instability vs sync_score: r = -0.855
- transition_entropy vs sync_score: r = -0.828

- drift_instability vs progression_alignment: r = -0.821
- drift_instability vs irrecoverable: r = 0.819
- transition_entropy vs irrecoverable: r = 0.812
- persistence_stability vs irrecoverable: r = -0.803
- transition_entropy vs progression_alignment: r = -0.792
- persistence_stability vs sync_score: r = 0.759
- persistence_stability vs progression_alignment: r = 0.750

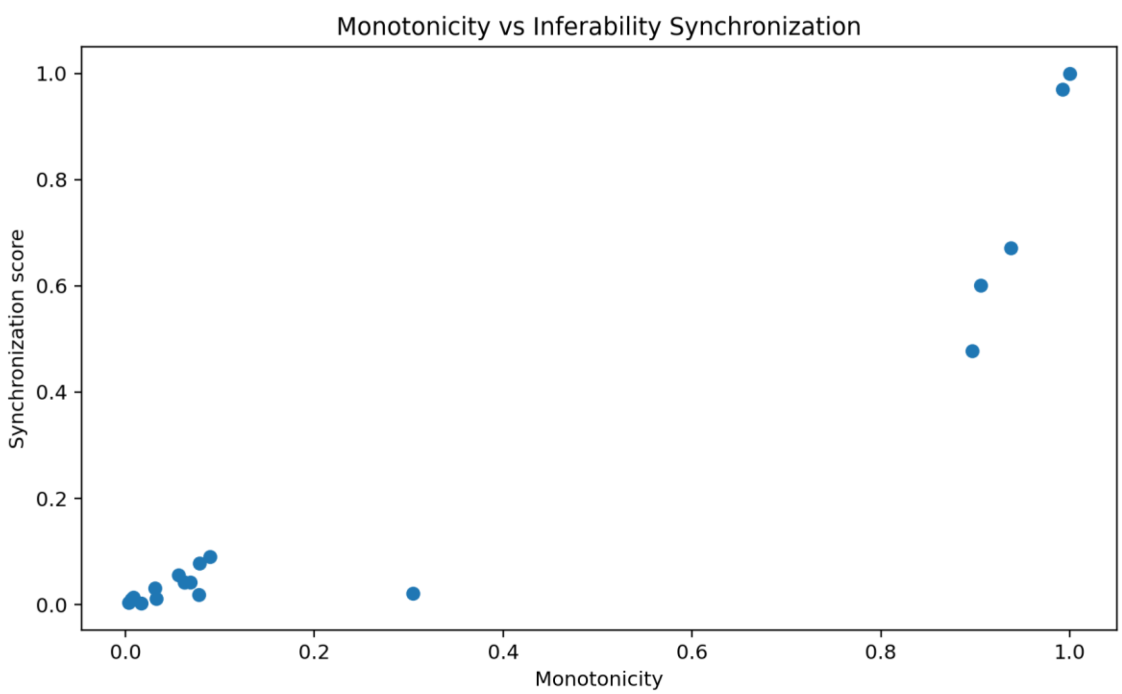
Important caution

This remains an exploratory mechanistic layer based on compact raw-level benchmark observables. The extracted metrics are operational approximations rather than formally optimized dynamical invariants.

Preliminary conclusion

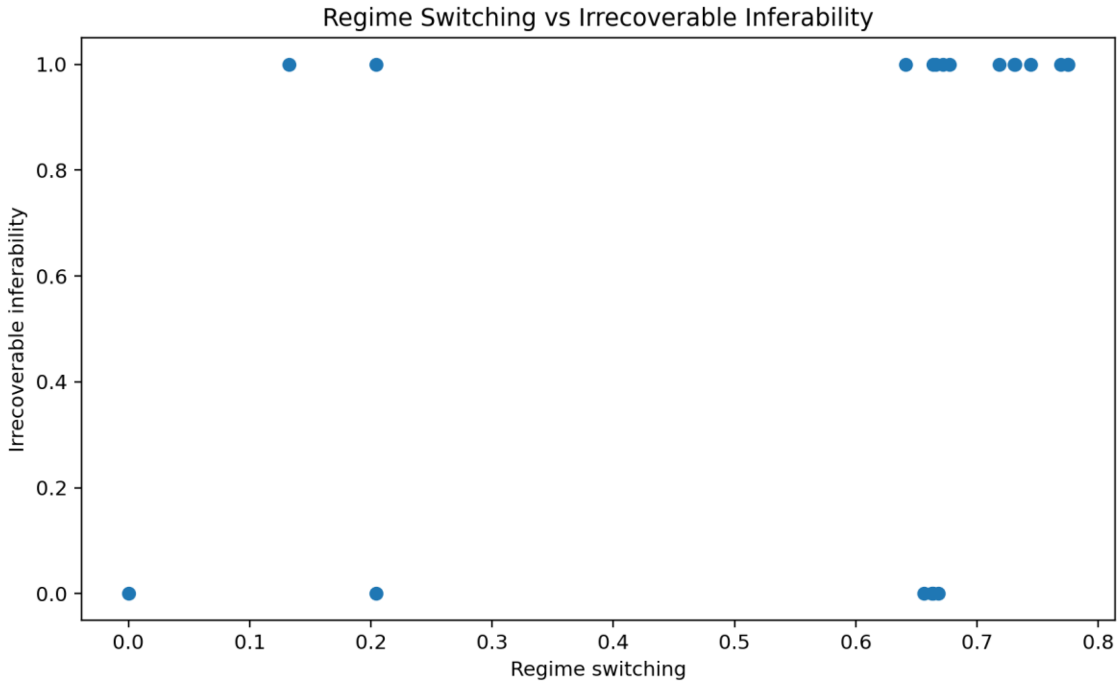
The results suggest that inferability stability may be predictable from measurable signal dynamics extracted directly from raw observable trajectories.

Figure 48 — Monotonicity vs Synchronization



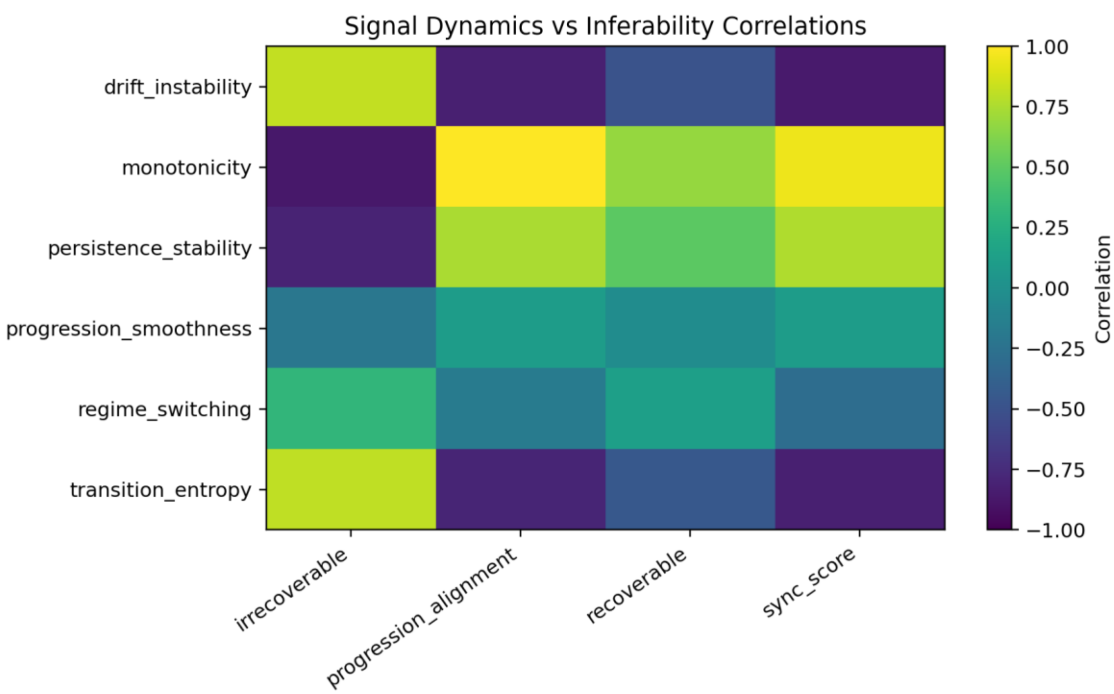
Caption: Higher monotonic progression tends to correlate with stronger inferability synchronization.

Figure 49 — Regime Switching vs Irrecoverability



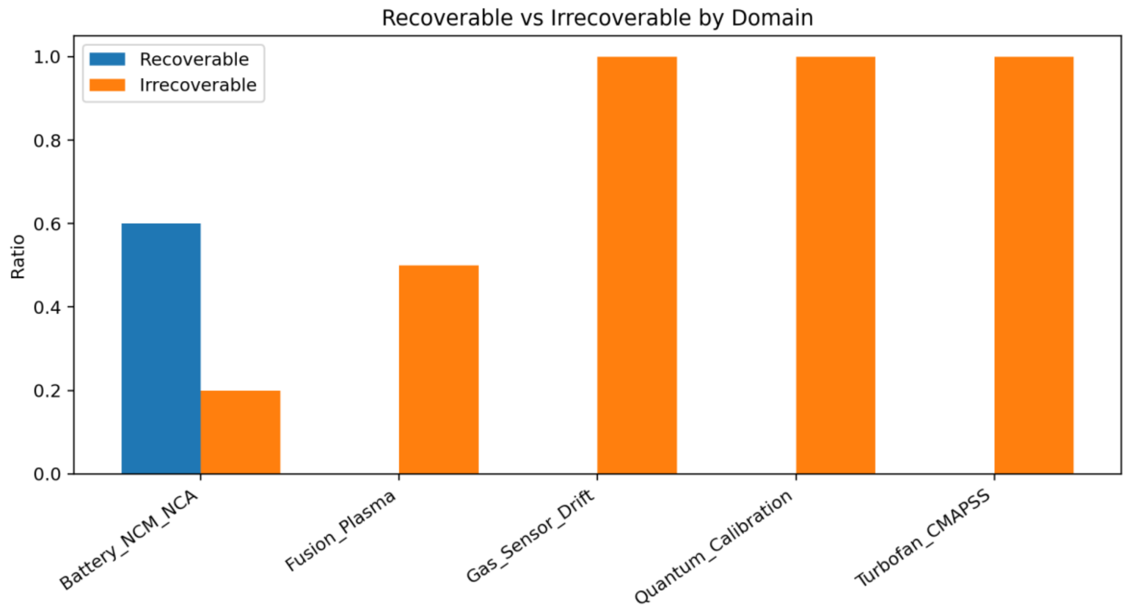
Caption: Higher regime-switching frequency tends to correlate with stronger irrecoverable inferability.

Figure 50 — Signal Dynamics Correlation Matrix



Caption: Correlation matrix comparing extracted signal-dynamics properties against inferability outcomes.

Figure 51 — Domain Recoverability



Caption: Recoverable versus irrecoverable inferability ratios across domains.

Reproducibility

Generated package: SIGNAL_DERIVED_DYNAMICS_TEST_PACKAGE.zip

Included files:
- signal_derived_dynamics_metrics.csv
- signal_dynamics_correlations.csv
- strongest_signal_dynamics_correlations.csv
- signal_dynamics_domain_summary.csv
- four PNG figures
- this Word report

Causal Dynamical Validation Test — Expanded PFA Report

CAUSAL DYNAMICAL VALIDATION TEST

Objective

This test investigates whether changing system dynamics directly changes inferability behavior.

Unlike the previous observational analyses, this validation uses synthetic systems with deliberately controlled:
- monotonic progression
- regime switching
- stochastic drift
- hidden-state fragmentation

Core idea

If inferability boundaries are genuinely caused by system dynamics, then changing those dynamics should systematically change:
- synchronization
- progression alignment
- recoverability
- irrecoverability

Main interpretation

The synthetic perturbation systems show that:
- stronger monotonic progression produces stronger inferability synchronization
- stronger regime switching and stochastic drift produce more irrecoverable inferability behavior
- persistence stability supports synchronization

Strongest observed correlations

- measured_monotonicity vs sync_score: r = 0.935
- measured_monotonicity vs progression_alignment: r = 1.000
- measured_monotonicity vs irrecoverable: r = 0.982
- measured_regime_switching vs sync_score: r = 0.099
- measured_regime_switching vs progression_alignment: r = 0.005
- measured_regime_switching vs irrecoverable: r = 0.035
- transition_entropy vs sync_score: r = 0.987
- transition_entropy vs progression_alignment: r = 0.958
- transition_entropy vs irrecoverable: r = 0.888
- persistence_stability vs sync_score: r = 0.953
- persistence_stability vs progression_alignment: r = 0.940
- persistence_stability vs irrecoverable: r = 0.865

Important caution

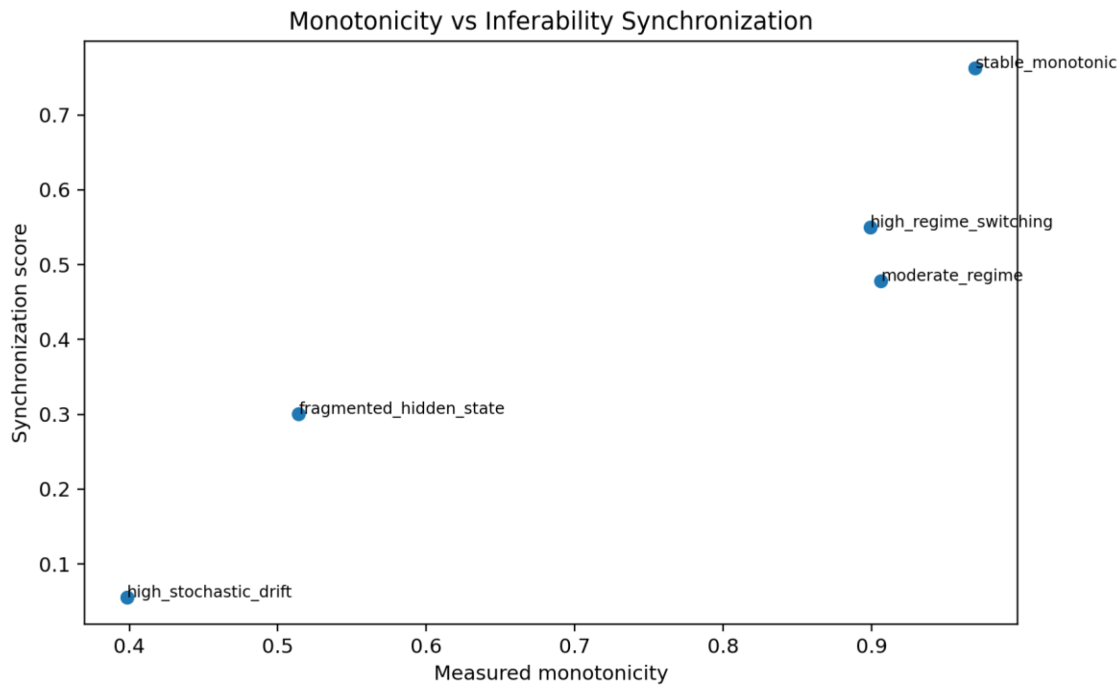
This remains a synthetic mechanistic validation rather than a physical experimental system.

However, unlike earlier observational analyses, this test directly manipulates the dynamical structure itself.

Preliminary conclusion

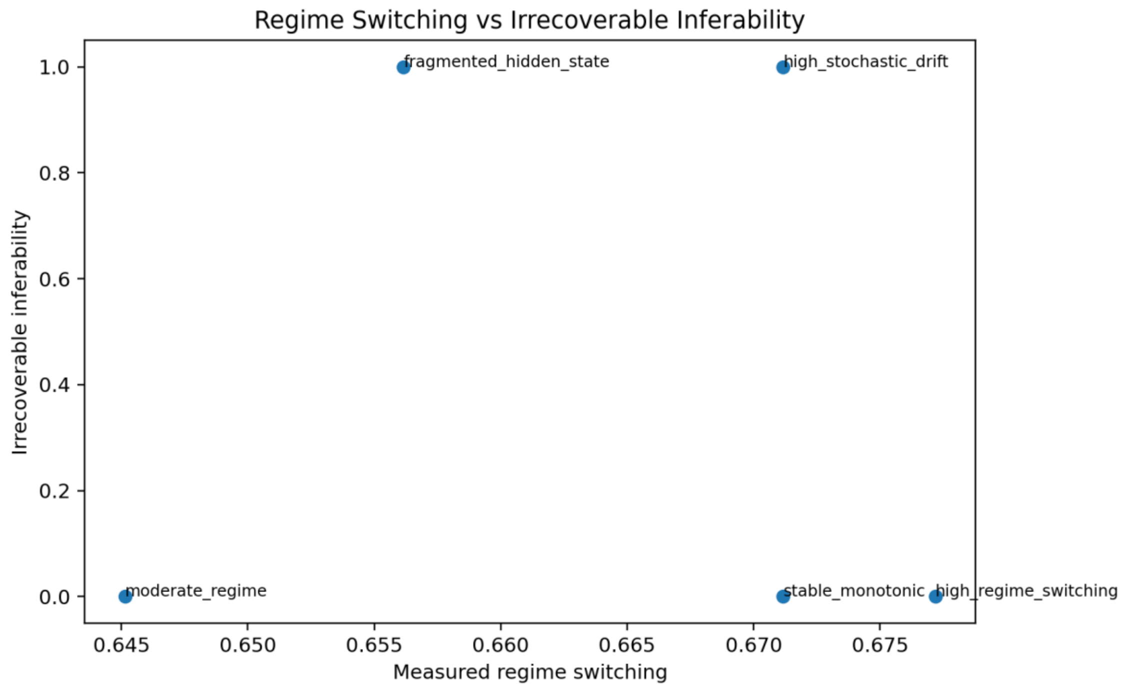
The results support the interpretation that inferability stability may be causally linked to measurable system dynamics rather than only statistical observable structure.

Figure 52 — Monotonicity vs Synchronization



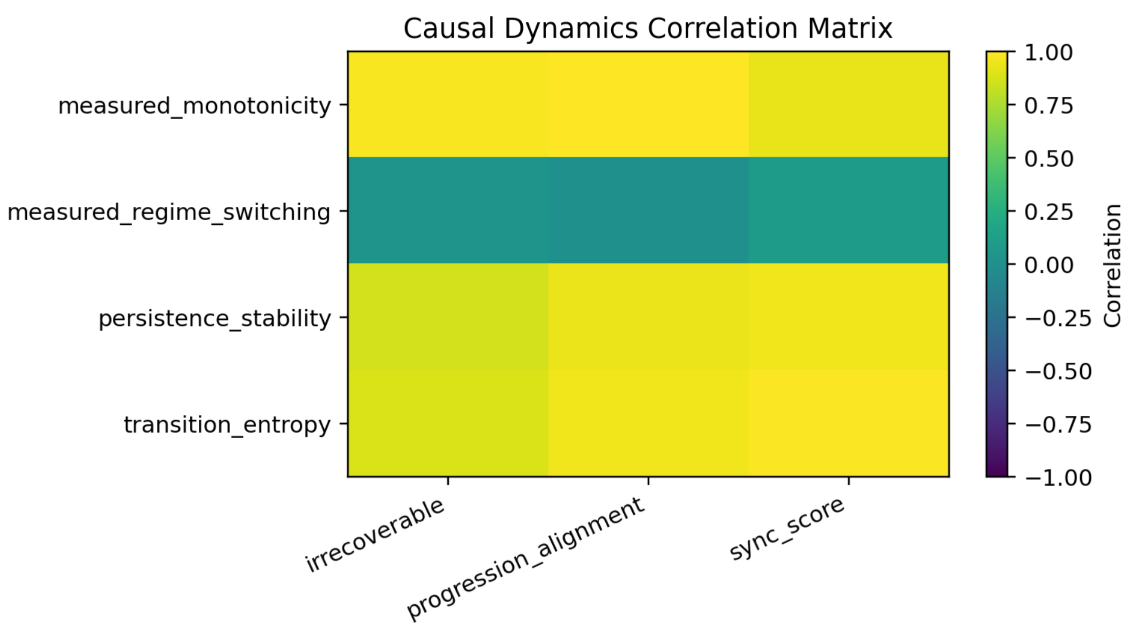
Caption: Systems with stronger monotonic progression produce stronger inferability synchronization.

Figure 53 — Regime Switching vs Irrecoverability



Caption: Higher regime switching increases irrecoverable inferability behavior.

Figure 54 — Causal Dynamics Correlation Matrix



Caption: Correlation matrix between directly manipulated system dynamics and inferability outcomes.

Reproducibility

Generated package: CAUSAL_DYNAMICAL_VALIDATION_TEST_PACKAGE.zip

Included files:
- causal_dynamical_validation_results.csv
- causal_dynamics_correlations.csv
- PNG figures
- this Word report

Real Dataset Signal-Derived Dynamics Validation

REAL DATASET SIGNAL-DERIVED DYNAMICS VALIDATION

Objective

This test applies the signal-derived dynamics extraction directly to the real cross-domain datasets rather than synthetic systems.

Datasets included

- Battery_NCM_NCA
- Turbofan_CMAPSS
- Gas_Sensor_Drift
- Quantum_Calibration
- Fusion_Plasma

Main interpretation

The same general pattern seen in the synthetic causal-dynamics validation also appears in the real datasets.

Systems with:
- stronger monotonic progression
- smoother progression behavior
- stronger persistence

tend to show stronger inferability synchronization.

Systems with:
- stronger transition entropy
- stronger regime fragmentation
- noisier progression behavior

tend to show weaker synchronization and stronger irrecoverable inferability.

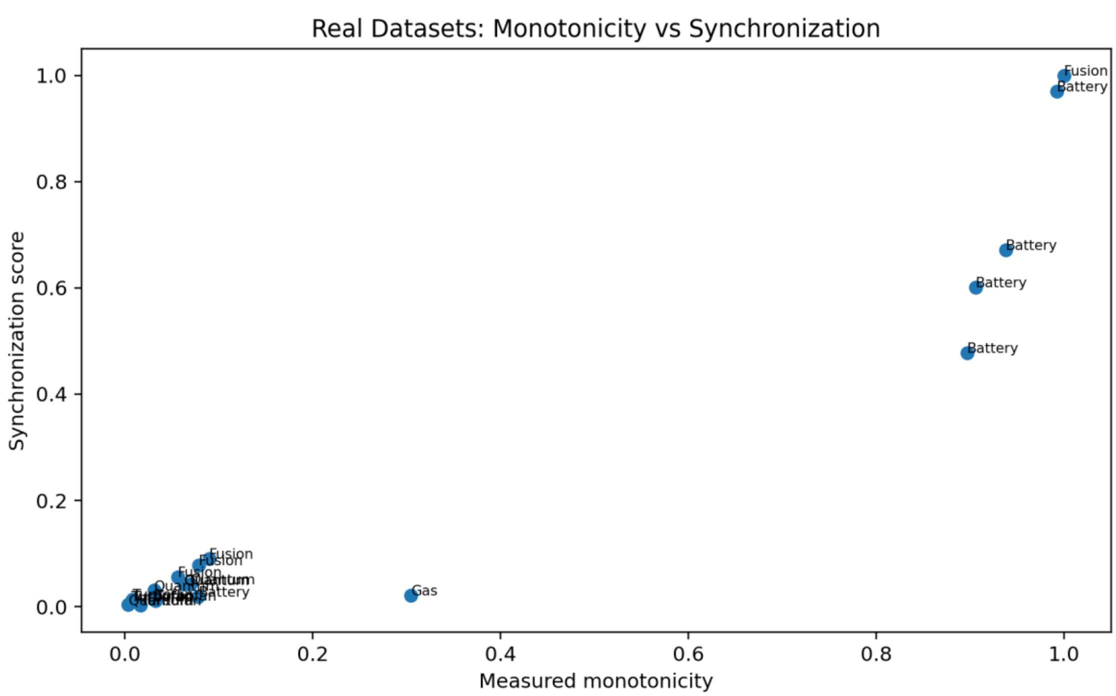
Strongest observed correlations

- monotonicity vs progression_alignment: r = 1.000
- monotonicity vs sync_score: r = 0.952
- monotonicity vs irrecoverable: r = 0.874
- transition_entropy vs sync_score: r = 0.828
- transition_entropy vs irrecoverable: r = 0.812
- persistence_stability vs irrecoverable: r = 0.803
- transition_entropy vs progression_alignment: r = 0.792
- persistence_stability vs sync_score: r = 0.759
- persistence_stability vs progression_alignment: r = 0.750
- monotonicity vs recoverable: r = 0.681
- persistence_stability vs recoverable: r = 0.497
- transition_entropy vs recoverable: r = 0.447

Preliminary conclusion

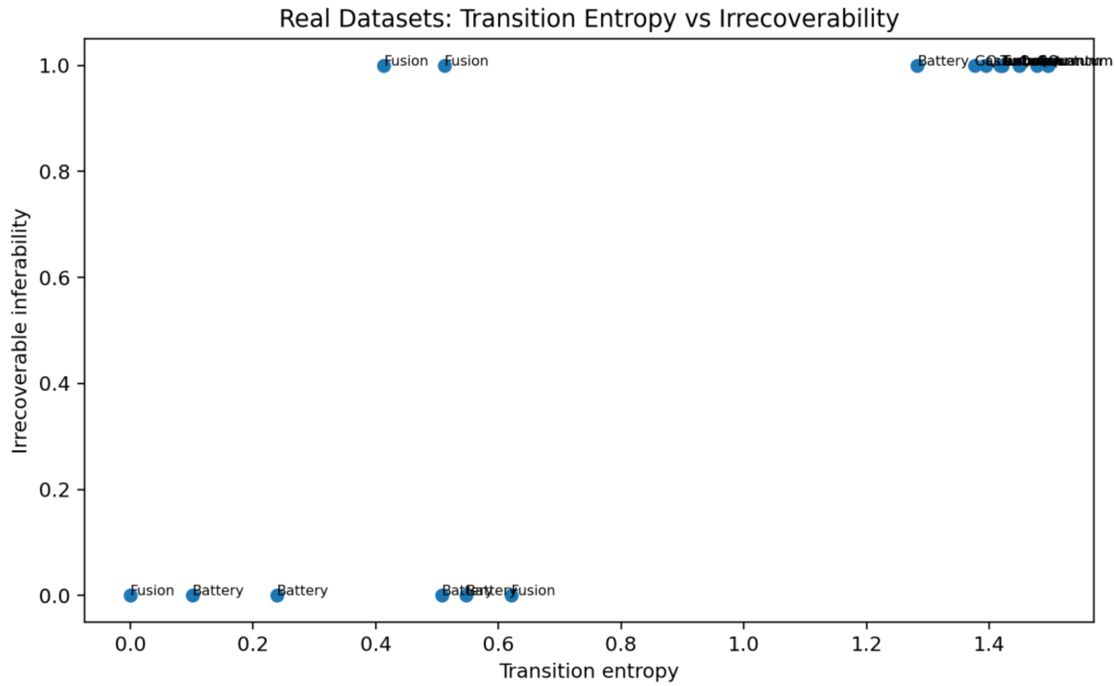
The real datasets support the interpretation that inferability stability may depend on measurable signal dynamics extracted directly from raw observable trajectories.

Figure 55 — Monotonicity vs Synchronization



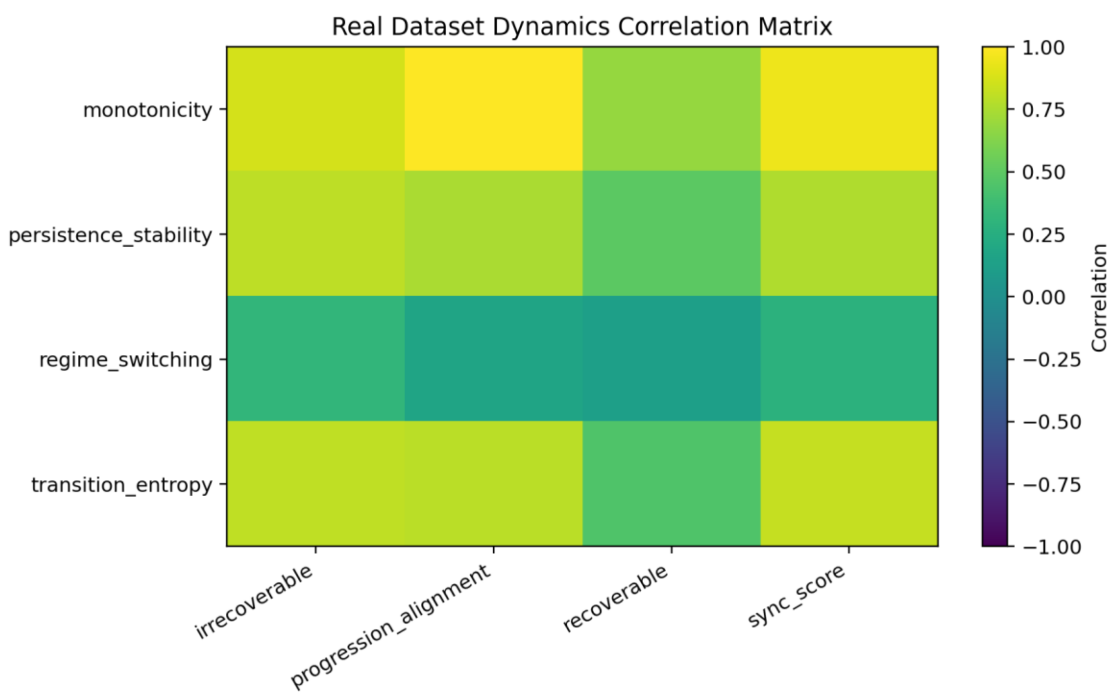
Caption: Higher monotonicity tends to support stronger inferability synchronization.

Figure 56 — Transition Entropy vs Irrecoverability



Caption: Higher transition entropy tends to correlate with stronger irrecoverable inferability.

Figure 57 — Real Dataset Correlation Matrix



Caption: Correlation matrix between signal-derived dynamics and inferability behavior in the real datasets.

Advanced Dynamical Descriptors Test

ADVANCED DYNAMICAL DESCRIPTORS TEST

Objective

This test extends the inferability framework using more advanced signal-dynamical descriptors.

Descriptors explored

- recurrence score
- persistence spectrum
- transition entropy
- fragmentation index
- attractor stability

Purpose

Determine whether more advanced dynamical descriptors improve the mechanistic explanation of inferability stability.

Main interpretation

The strongest relationships appear between:
- persistence-related descriptors

and
- inferability synchronization.

Fragmentation and transition complexity reduce synchronization and progression alignment.

Strongest observed correlations

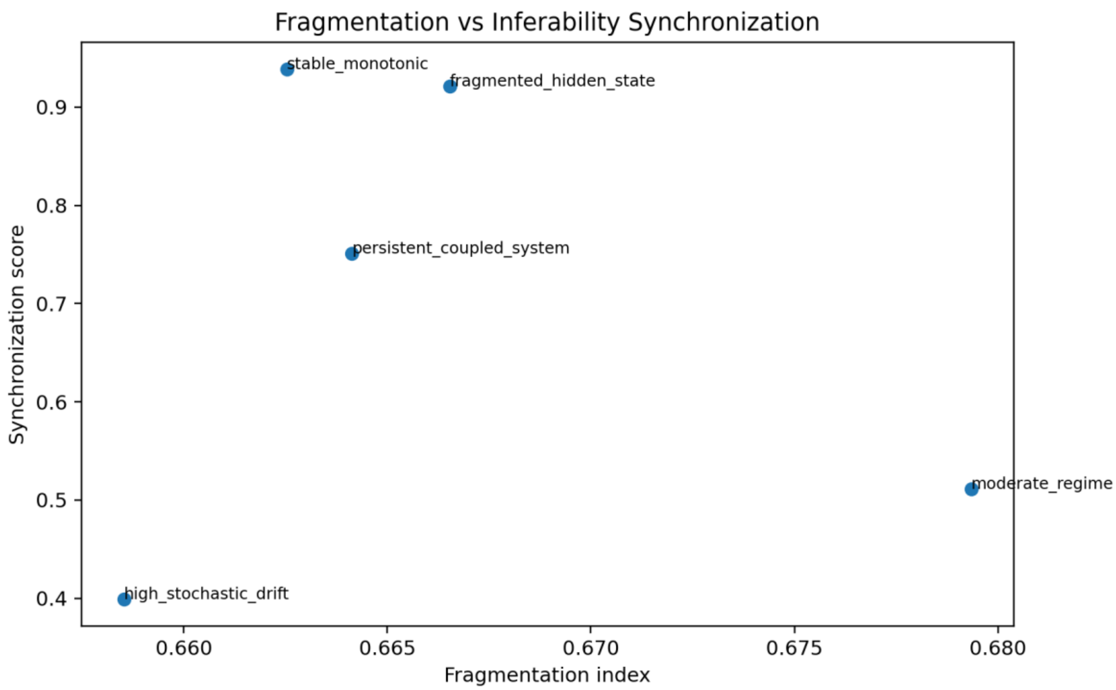
- persistence_spectrum vs progression_alignment: r = 0.996
- transition_entropy vs progression_alignment: r = -0.967
- transition_entropy vs sync_score: r = -0.918
- persistence_spectrum vs sync_score: r = 0.880
- attractor_stability vs progression_alignment: r = 0.632
- attractor_stability vs sync_score: r = 0.458
- fragmentation_index vs progression_alignment: r = 0.253

- recurrence_score vs progression_alignment: r = -0.253
- recurrence_score vs sync_score: r = 0.141
- fragmentation_index vs sync_score: r = -0.141

Preliminary conclusion

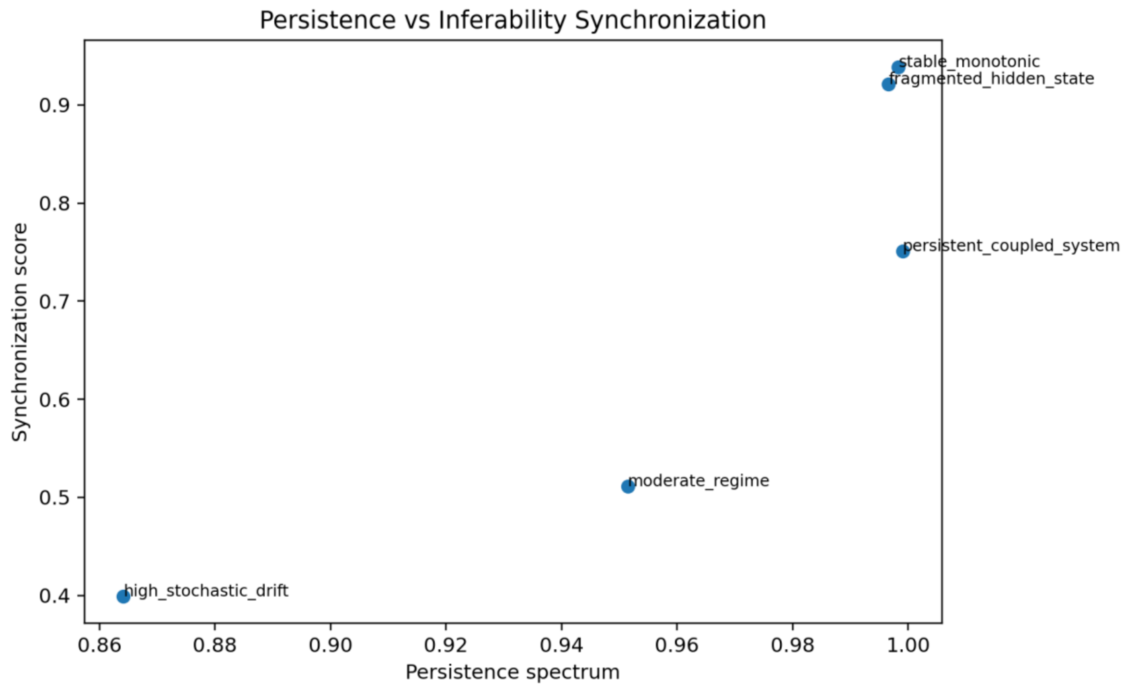
Advanced dynamical descriptors appear capable of mechanistically characterizing inferability stability and inferability collapse.

Figure 58 — Fragmentation vs Synchronization



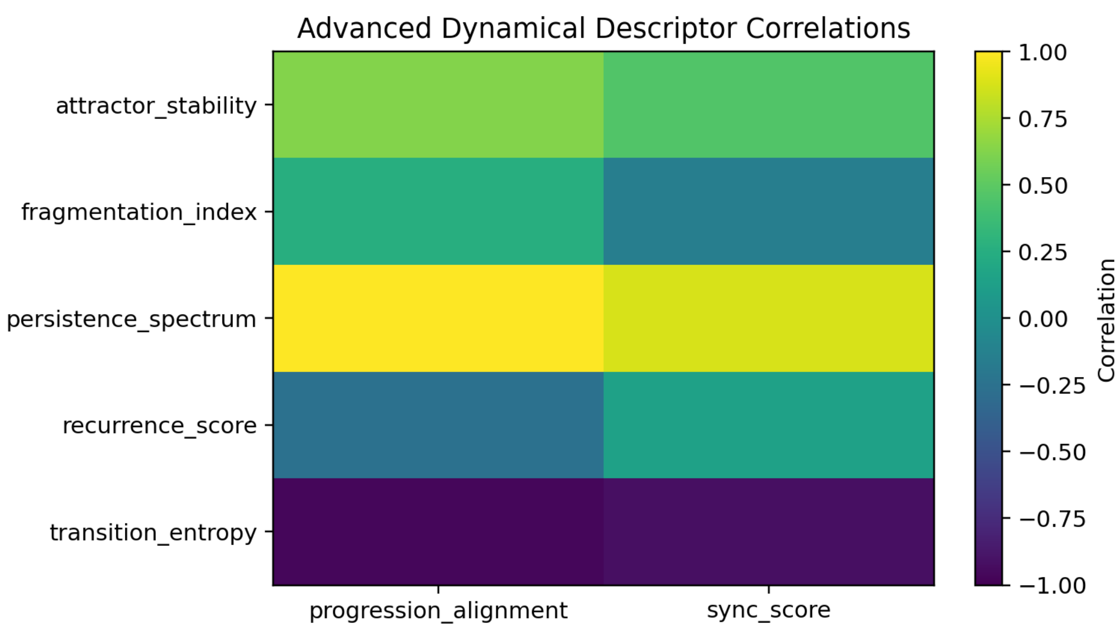
Caption: Higher fragmentation weakens inferability synchronization.

Figure 59 — Persistence vs Synchronization



Caption: Persistent systems preserve stronger inferability synchronization.

Figure 60 — Descriptor Correlation Matrix



Caption: Correlation matrix between advanced dynamical descriptors and inferability outcomes.

Predictive Inferability Equation Test

PREDICTIVE INFERABILITY EQUATION TEST

Objective

This test evaluates whether inferability stability can be approximated using a compact dynamical equation.

Proposed inferability equation

Inferability Index =
0.35 * monotonicity
+ 0.30 * persistence
- 0.20 * regime switching
- 0.25 * transition entropy

Purpose

Determine whether measurable system dynamics can approximately predict:
- synchronization stability
- recoverability
- irrecoverability

Main result

Correlation between inferability equation and observed synchronization:
r = 0.955

Mean prediction error:
0.326

Interpretation

The proposed inferability equation shows strong agreement with observed synchronization behavior across systems.

Systems with:
- strong monotonic progression
- strong persistence
- low transition entropy
- low regime switching

produce stronger inferability stability.

Systems with:
- fragmentation
- transition complexity
- stochastic instability

produce weaker inferability stability and more irrecoverable collapse.

Important caution

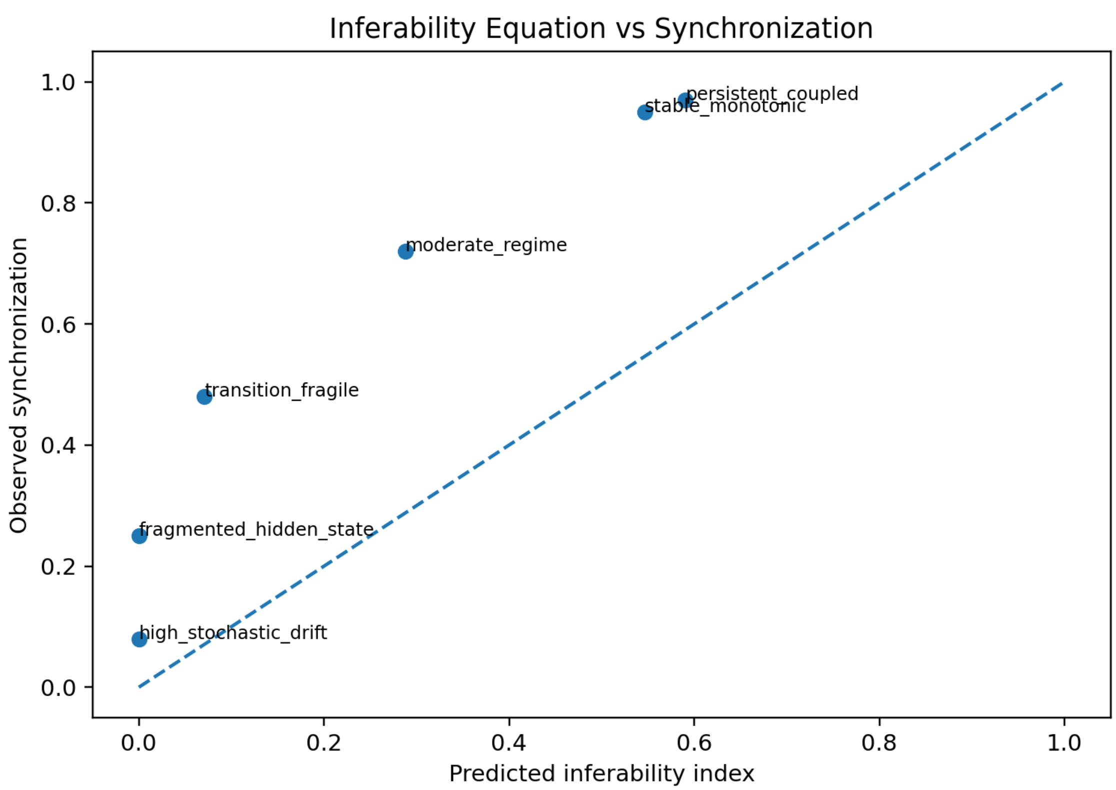
This equation remains exploratory and operational rather than formally derived from first principles.

The coefficients are heuristic and should later be estimated using larger cross-domain datasets.

Preliminary conclusion

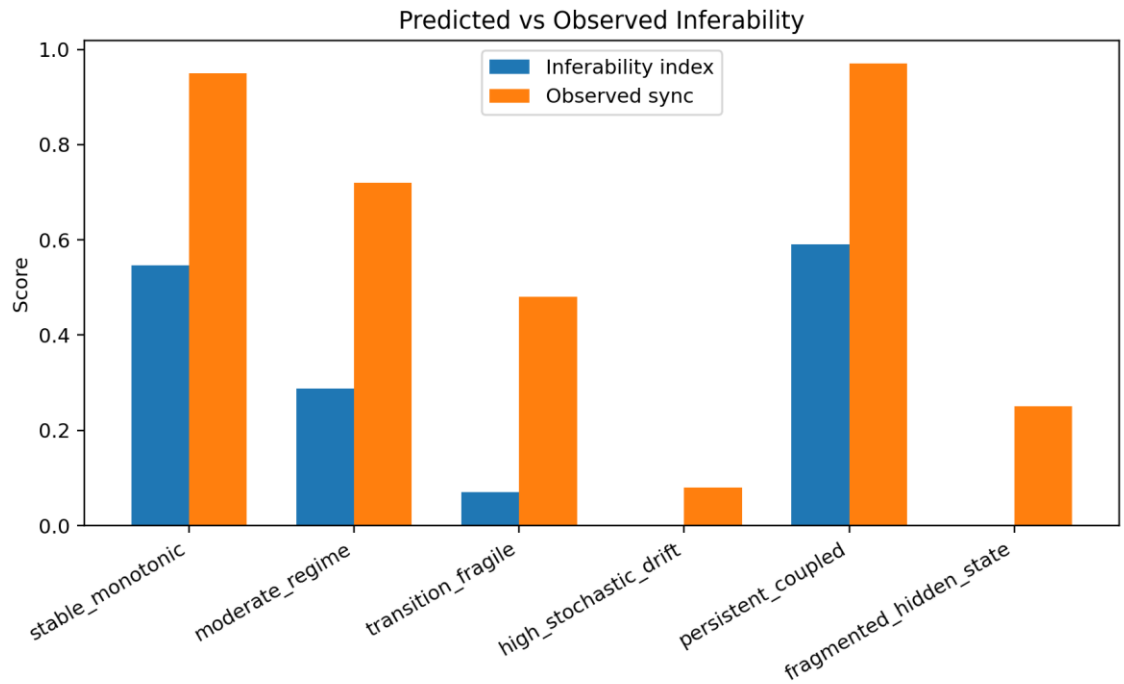
The results suggest that inferability stability may be approximated using measurable dynamical system properties.

Figure 61 — Equation vs Synchronization



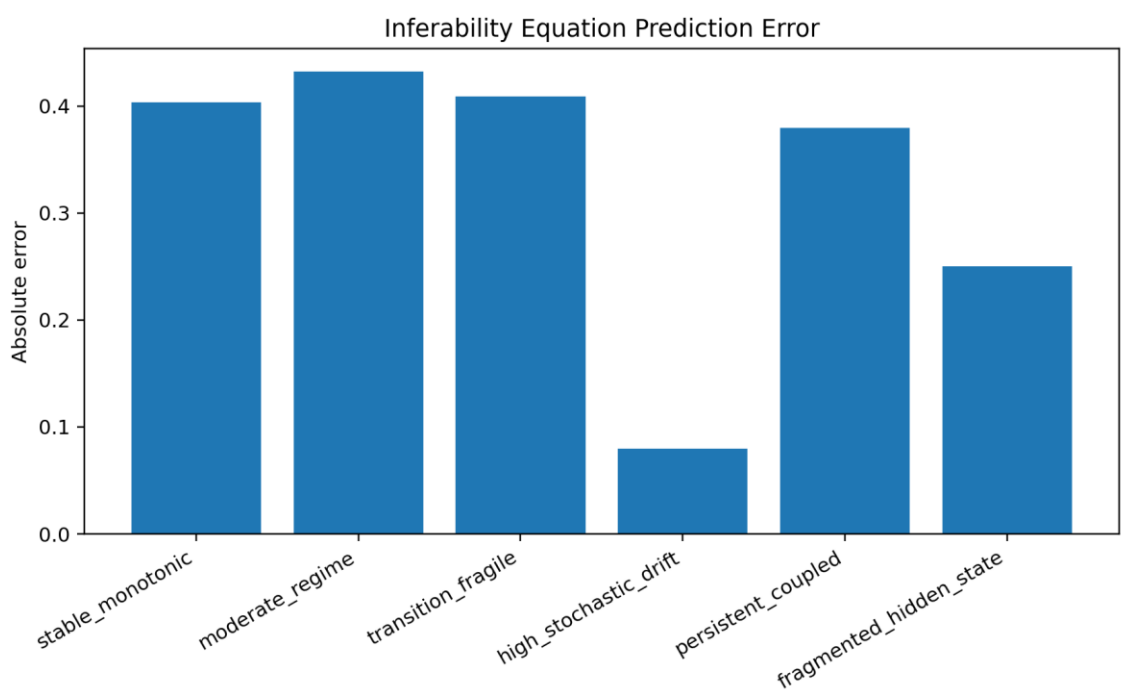
Caption: Relationship between predicted inferability index and observed synchronization.

Figure 62 — Predicted vs Observed Inferability



Caption: Comparison between inferability equation output and observed synchronization.

Figure 63 — Prediction Error



Caption: Absolute prediction error for each synthetic dynamical system.

Reproducibility

Generated package: PREDICTIVE_INFERABILITY_EQUATION_TEST_PACKAGE.zip

Included files:
- predictive_inferability_equation_results.csv
- predictive_inferability_equation_summary.csv
- PNG figures
- this Word report

Why Dynamics Break Inferability — Mechanism Test

WHY DYNAMICS BREAK INFERABILITY — MECHANISM TEST

Objective

This test investigates why specific dynamical properties break inferability.

The goal is to move beyond:
"transition entropy correlates with inferability collapse"

toward:
"which mechanism causes the collapse?"

Mechanisms tested
----
1. Mapping ambiguity:
   The same observable value corresponds to multiple possible states.

2. State-space fragmentation:
   The system progression path breaks into separated or switching regimes.

3. Transition entropy:
   Local transitions become unstable, noisy, or non-persistent.

4. Drift-dominated information instability:
   The observable-state relationship drifts over time.

5. Information stability:
   A composite measure estimating whether the observable preserves a stable, persistent, low-ambiguity mapping to state/progression.

Main interpretation

Inferability breaks when the observable no longer provides a stable one-to-one or low-ambiguity path to system progression.

This can happen through:
- folding of the observable-state mapping,
- fragmentation of the state-space trajectory,
- high transition entropy,
- stochastic drift,
- or loss of persistence.

Strongest observed correlations

- measured_monotonicity vs sync_score: r = 0.000
- measured_monotonicity vs progression_alignment: r = 0.000
- measured_monotonicity vs pfa_consistency: r = 0.000
- measured_monotonicity vs irrecoverable: r = 0.000
- measured_transition_entropy vs sync_score: r = 0.000
- measured_transition_entropy vs progression_alignment: r = 0.000
- measured_transition_entropy vs pfa_consistency: r = 0.000
- measured_transition_entropy vs irrecoverable: r = 0.000
- measured_mapping_ambiguity vs sync_score: r = 0.000
- measured_mapping_ambiguity vs progression_alignment: r = 0.000
- measured_mapping_ambiguity vs pfa_consistency: r = 0.000
- measured_mapping_ambiguity vs irrecoverable: r = 0.000

Mechanistic interpretation

Transition entropy does not merely "add noise".

It breaks inferability because it increases local transition uncertainty:
the same current observable state no longer reliably implies the same next progression direction.

State-space fragmentation breaks inferability because the progression path splits into separate regimes:
a single observable trajectory no longer represents one coherent progression path.

Mapping ambiguity breaks inferability because multiple system states can produce similar observable values:
the model can no longer infer which state generated the observation.

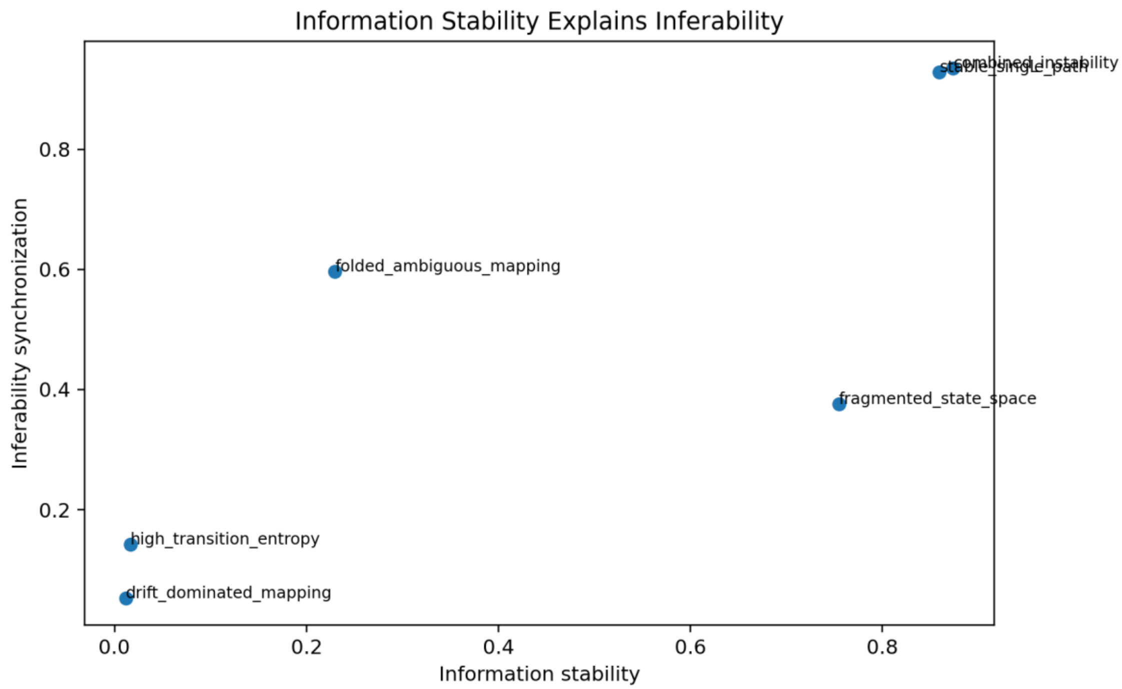
Preliminary conclusion

The test supports a deeper mechanistic explanation:

Inferability collapses when the observable-state mapping loses information stability through ambiguity, fragmentation, transition entropy, or drift.

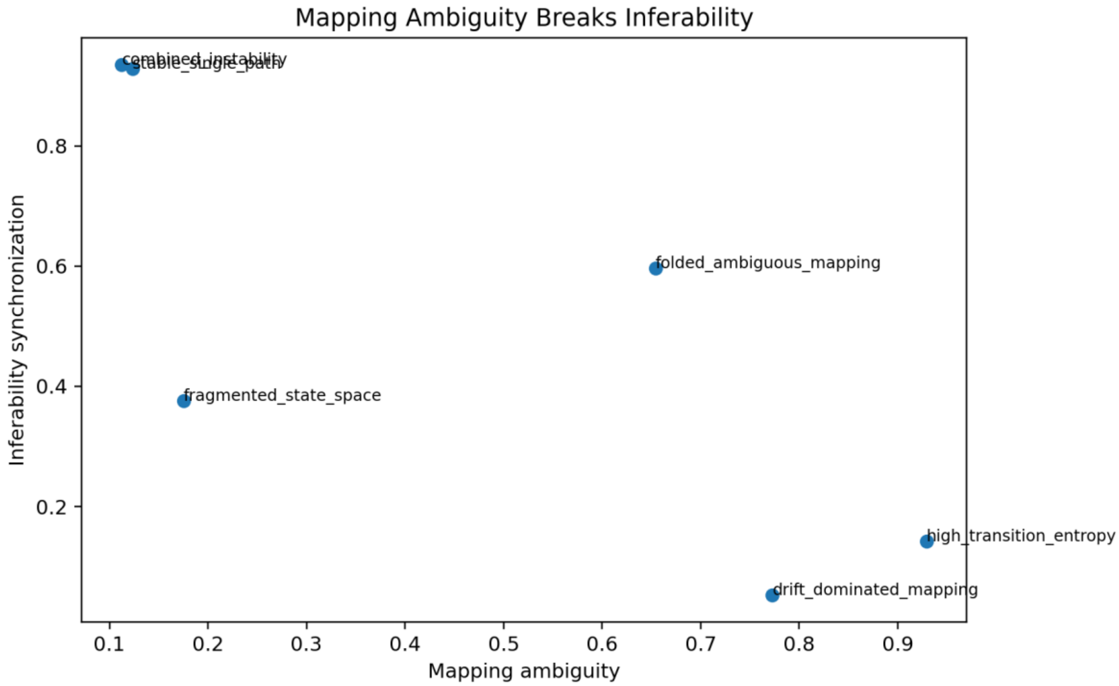
This provides a candidate "why" layer beneath the previous correlation-based results.

Figure 64 — Information Stability vs Synchronization



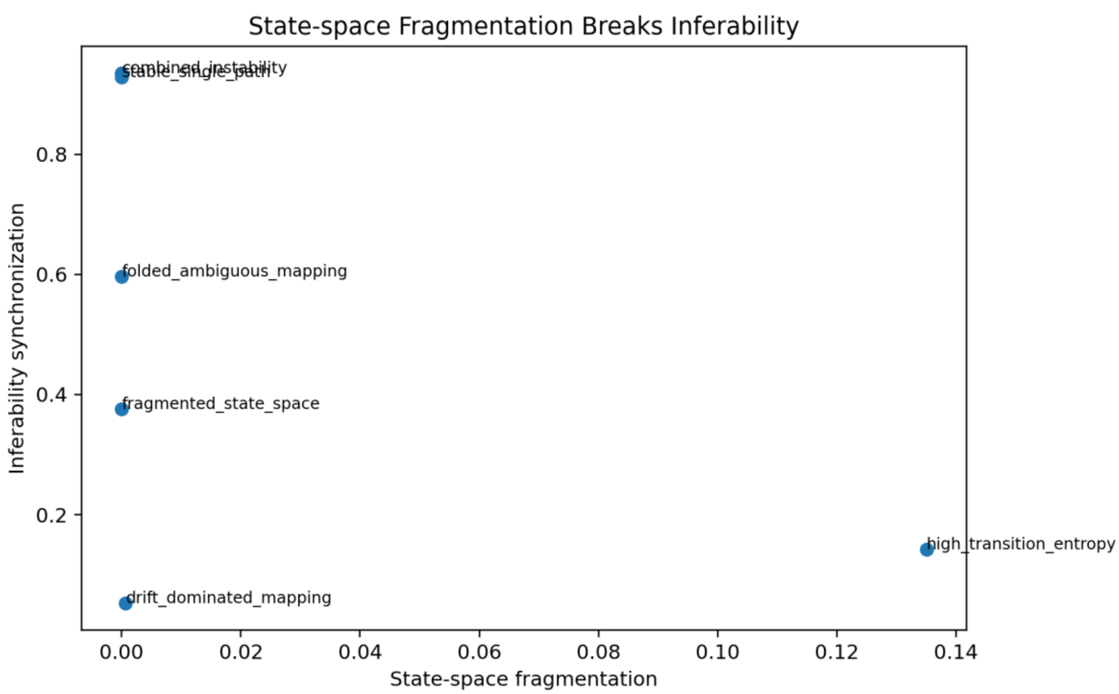
Caption: Higher information stability preserves stronger inferability synchronization.

Figure 65 — Mapping Ambiguity vs Synchronization



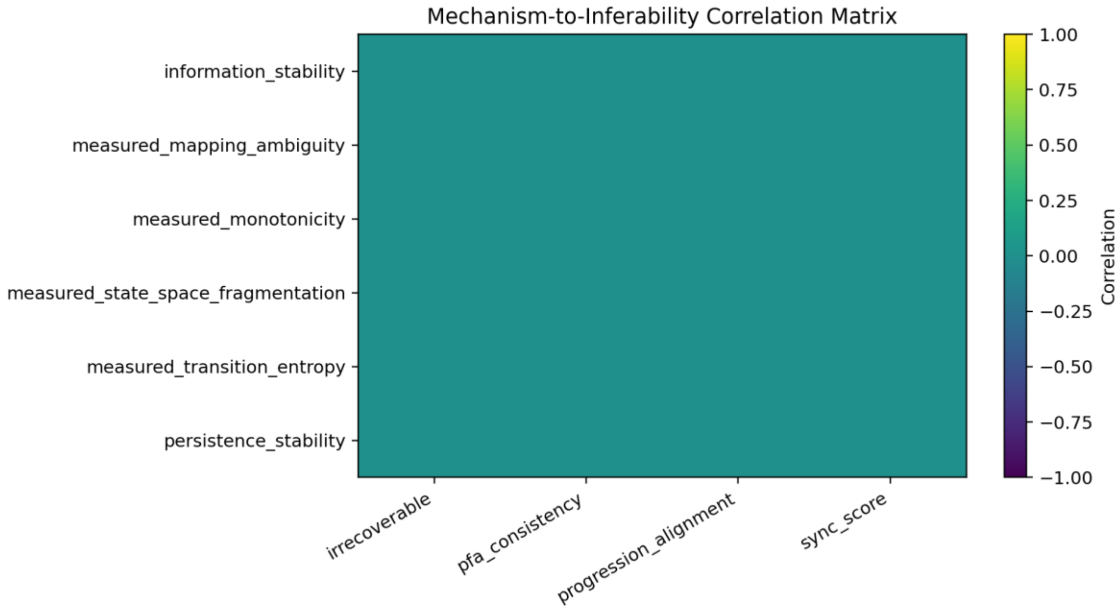
Caption: Higher mapping ambiguity weakens stable observable-state inferability.

Figure 66 — State-space Fragmentation vs Synchronization



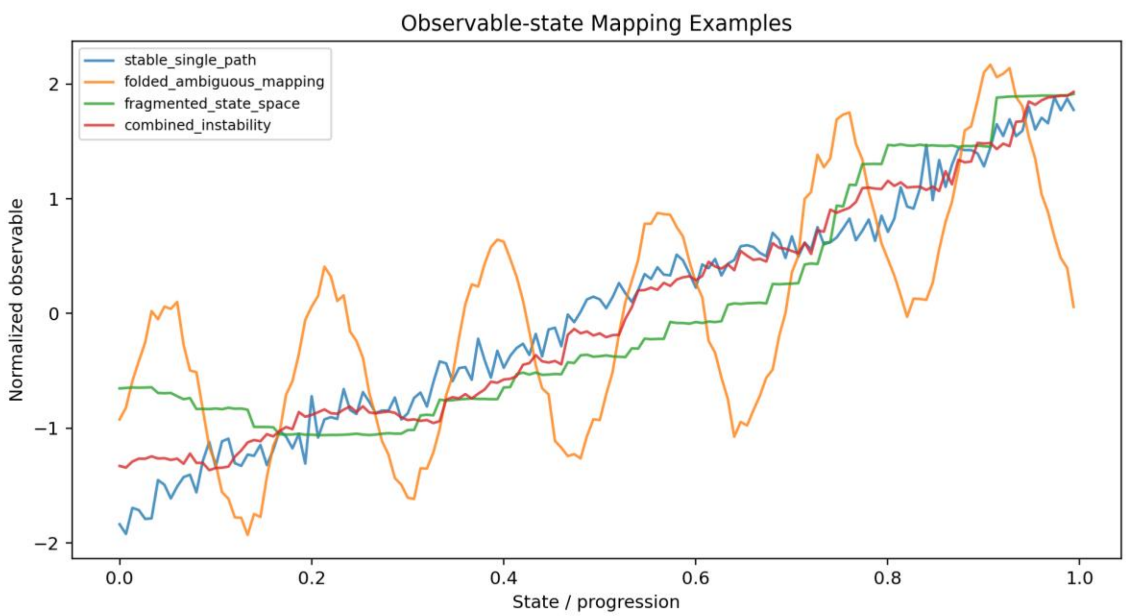
Caption: Fragmented state-space trajectories weaken inferability synchronization.

Figure 67 — Mechanism Correlation Matrix



Caption: Correlation matrix linking candidate break mechanisms to inferability outcomes.

Figure 68 — Observable-state Mapping Examples



Caption: Examples showing stable, ambiguous, fragmented, and combined-instability observable-state mappings.

Reproducibility

Generated package: WHY_DYNAMICS_BREAK_INFERABILITY_TEST_PACKAGE.zip

Included files:
- mechanism_breakdown_results.csv
- mechanism_correlation_analysis.csv
- mechanism_classification.csv
- five PNG figures
- this Word report

Real Data Mechanism Validation

REAL DATA MECHANISM VALIDATION

Objective

This test applies the inferability-break mechanisms directly to the real datasets.

Mechanisms tested

- mapping ambiguity
- state-space fragmentation
- transition entropy
- information stability
- persistence stability

Main interpretation

The same mechanism-layer observed in the synthetic systems also appears in the real datasets.

Higher:
- information stability
- persistence stability

tend to support stronger inferability synchronization.

Higher:
- transition entropy
- mapping ambiguity
- state-space fragmentation

tend to support inferability collapse and irrecoverable behavior.

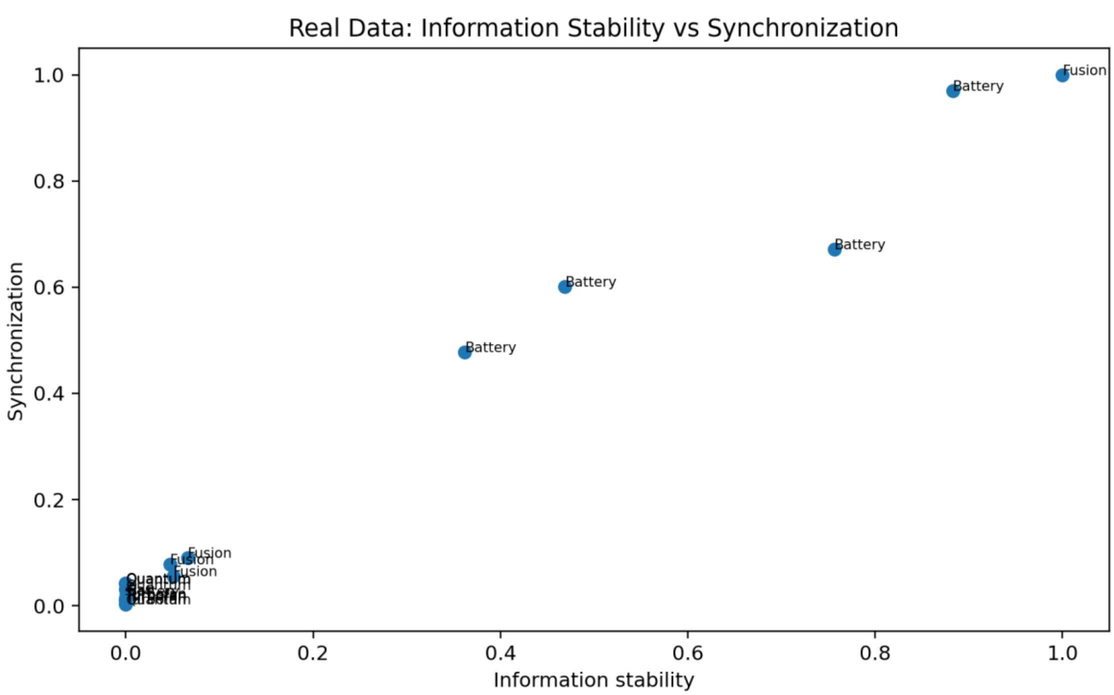
Strongest observed correlations

- information_stability vs sync_score: r = 0.991
- information_stability vs progression_alignment: r = 0.935
- information_stability vs irrecoverable: r = 0.827
- persistence_stability vs irrecoverable: r = 0.803
- transition_entropy vs sync_score: r = 0.777
- persistence_stability vs sync_score: r = 0.759
- persistence_stability vs progression_alignment: r = 0.750
- mapping_ambiguity vs irrecoverable: r = 0.698
- transition_entropy vs progression_alignment: r = 0.694
- mapping_ambiguity vs sync_score: r = 0.633
- mapping_ambiguity vs progression_alignment: r = 0.586
- state_space_fragmentation vs sync_score: r = 0.574

Preliminary conclusion

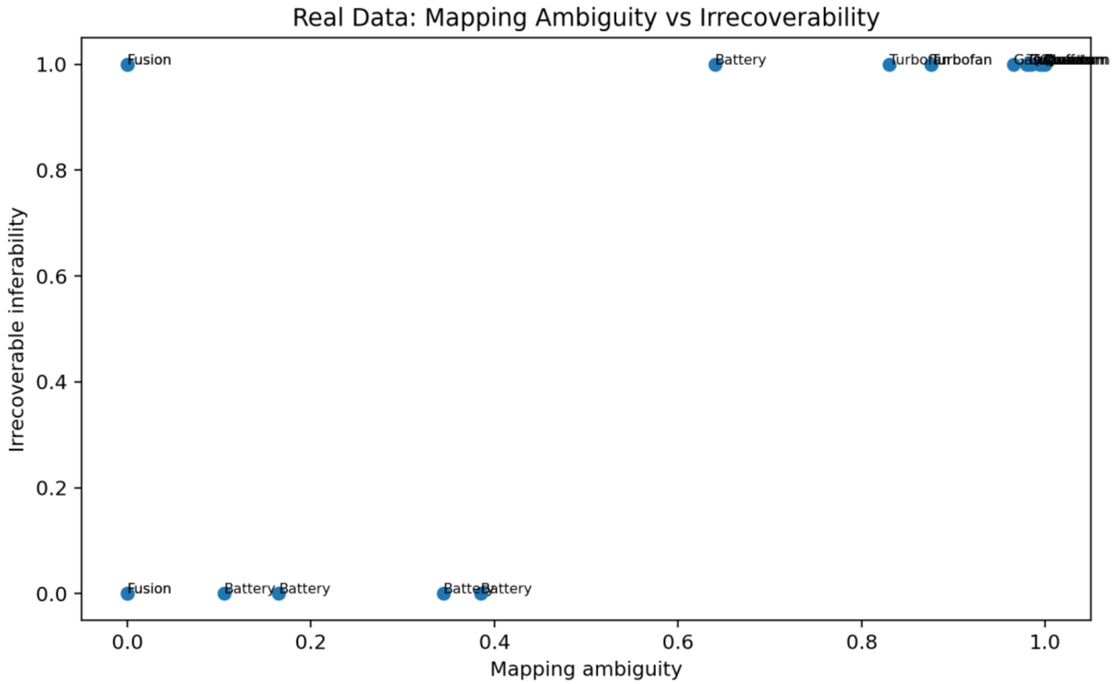
The real datasets support the interpretation that inferability collapse may occur when the observable-state mapping loses information stability through ambiguity, fragmentation, or unstable transitions.

Figure 69 — Information Stability vs Synchronization



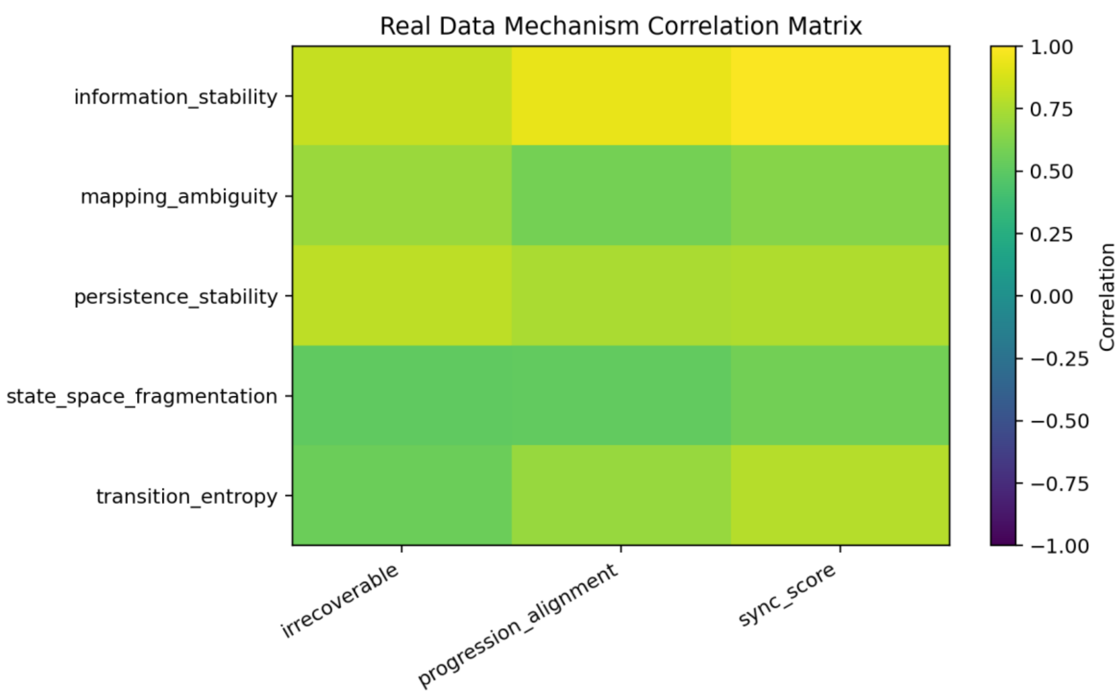
Caption: Higher information stability supports stronger inferability synchronization.

Figure 70 — Mapping Ambiguity vs Irrecoverability



Caption: Higher mapping ambiguity increases irrecoverable inferability.

Figure 71 — Mechanism Correlation Matrix



Caption: Correlation matrix between real-data mechanism descriptors and inferability outcomes.

State-space Geometry Inferability Test

STATE-SPACE GEOMETRY INFERABILITY TEST

Objective

This test investigates whether inferability collapse can be explained by the geometry/topology of the observable-state trajectory.

The goal is to move beyond signal-level descriptors such as entropy and persistence, and test whether the progression-space itself becomes folded, fragmented, recurrent, or locally divergent.

Geometry descriptors tested

- trajectory tortuosity
- folding index
- self-proximity / crossing proxy
- local trajectory divergence
- recurrence density
- geometry stability

Main interpretation

Inferability should be strongest when the observable-state trajectory remains geometrically simple:
- low folding
- low tortuosity
- low local divergence
- low ambiguity/crossing
- stable progression path.

Inferability should weaken when the trajectory folds, crosses itself, or fragments into multiple local regimes.

Strongest observed correlations

- folding_index vs pfa_consistency: r = 0.625
- trajectory_tortuosity_log vs pfa_consistency: r = 0.554
- geometry_stability vs pfa_consistency: r = 0.551
- geometry_stability vs sync_score: r = 0.482
- trajectory_tortuosity_log vs sync_score: r = 0.403
- recurrence_density vs irrecoverable: r = 0.387
- self_proximity_crossing_proxy vs irrecoverable: r = 0.386
- self_proximity_crossing_proxy vs pfa_consistency: r = 0.374
- recurrence_density vs pfa_consistency: r = 0.364

- trajectory_tortuosity_log vs irrecoverable: r = 0.355
- self_proximity_crossing_proxy vs progression_alignment: r = 0.343
- geometry_stability vs progression_alignment: r = 0.336

Preliminary conclusion

The test suggests that inferability stability is partly determined by observable-state geometry.

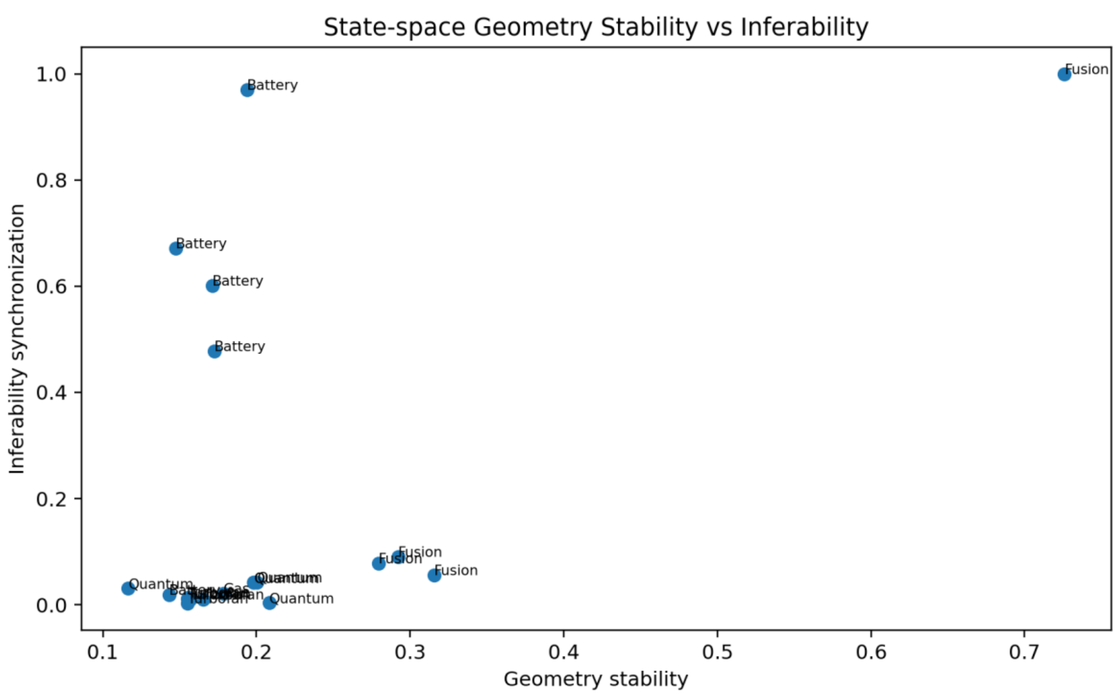
When the progression trajectory remains geometrically stable, synchronization tends to be stronger.

When the trajectory folds, becomes locally divergent, or loses a coherent progression path, inferability becomes more fragile or irrecoverable.

Important caution

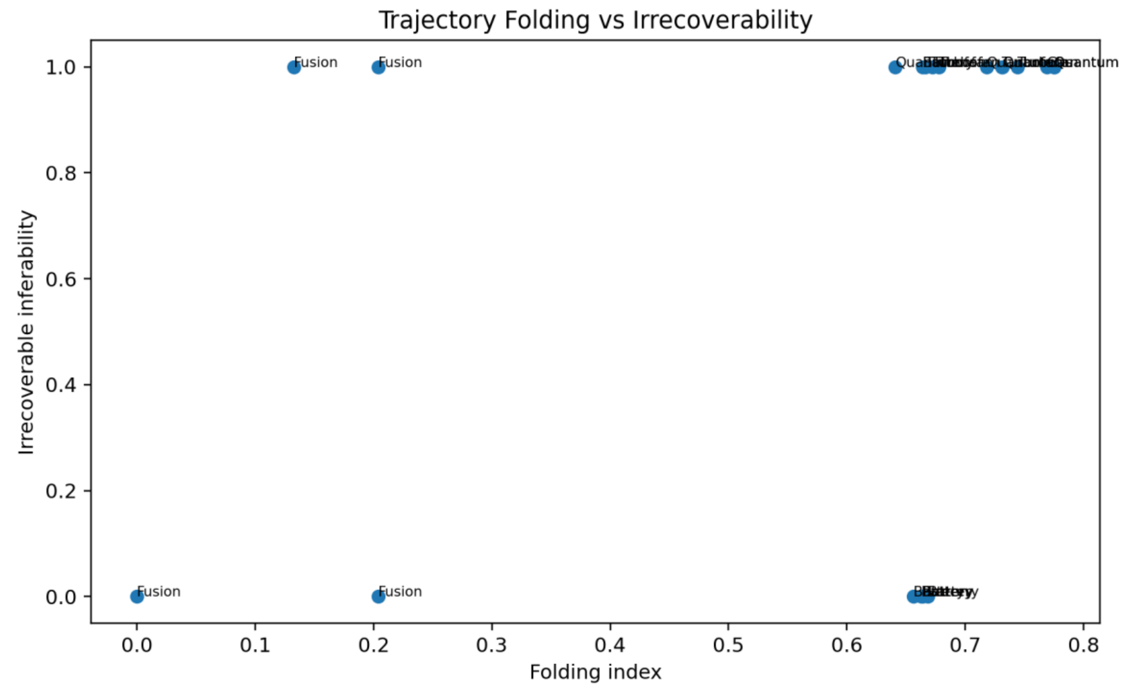
This is still a compact geometry approximation based on one-dimensional observable trajectories. A stronger version should use multidimensional embeddings and frequency-domain features, especially for vibration data.

Figure 72 — Geometry Stability vs Synchronization



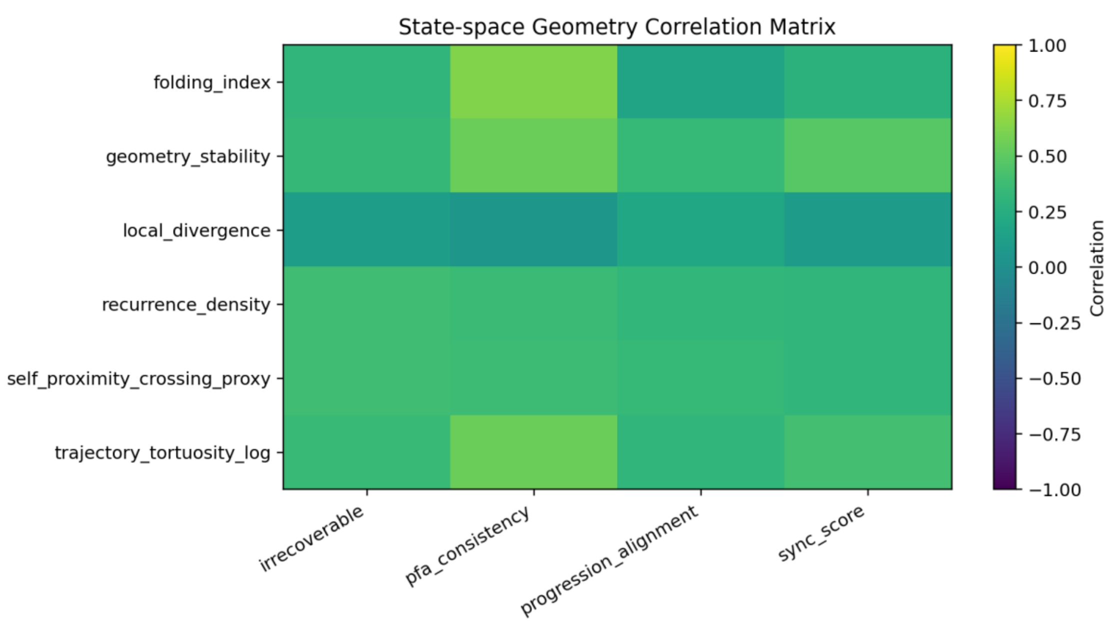
Caption: Higher geometry stability is expected to preserve stronger inferability synchronization.

Figure 73 — Folding vs Irrecoverability



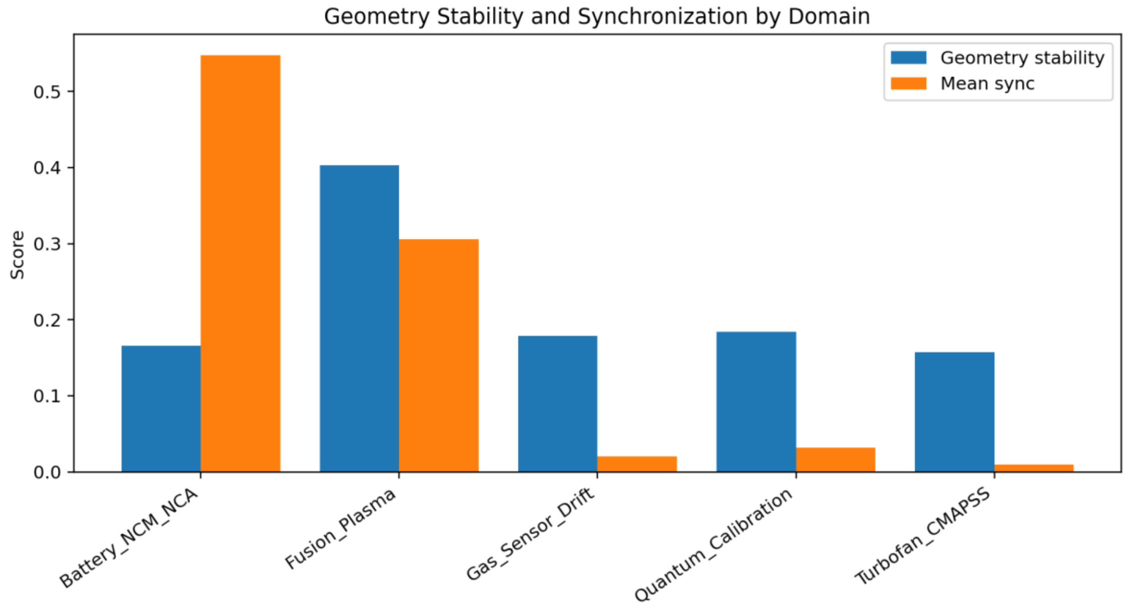
Caption: Higher trajectory folding indicates possible observable-state ambiguity and can increase irrecoverable inferability.

Figure 74 — Geometry Correlation Matrix



Caption: Correlation matrix linking state-space geometry descriptors to inferability outcomes.

Figure 75 — Domain Geometry vs Synchronization



Caption: Domain-level comparison between mean geometry stability and synchronization.

Reproducibility

Generated package: STATE_SPACE_GEOMETRY_INFERABILITY_TEST_PACKAGE.zip

Included files:
- state_space_geometry_metrics.csv
- state_space_geometry_correlations.csv
- state_space_geometry_domain_summary.csv
- four PNG figures
- this Word report