

Research Article

Beyond Autonomic Amplitude: A Two-Domain Framework of Dimensional Collapse and Cross-Domain Resilience

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1. Independent researcher

Standard heart rate variability (HRV) metrics capture how far the autonomic system moves between states (excursion) but not in how many independent directions it moves (dimensionality). The Response Repertoire Index (RRI-D) quantifies dimensionality as a Hill number of order 2 of the eigenvalue spectrum of four HRV features measured across standardized states; a preregistered test in 41 healthy adults found it computable, acceptably reliable at group level and unrelated to excursion. This framework paper connects the construct to resilience research, where resilience is understood as a process of adaptation, and positions RRI-D as a candidate marker of regulatory latitude, not as a resilience measure. It states three falsifiable hypotheses: (H1) under sustained load RRI-D declines while resting RMSSD stays practically unchanged, a possible counterpart of critical slowing down; (H2) interventions acting on amplitude and interventions acting on multi-state regulation dissociate on excursion versus RRI-D; (H3) autonomic dimensionality and a psychological repertoire index (RRI-R) relate to strain and recovery in additive, multiplicative or threshold form. Simulations of the registered algorithm show that RRI-D orders true dimensionality at group level, that measurement noise inflates it at low excursion, and that the observed near-zero correlation with excursion is what independence plus noise predicts. They also give sample sizes: 36 persons with five sessions detect a within-person decline of 0.1 units with 84% power, whereas distinguishing the H3 models needs 200 to 400 persons. We propose a minimal multi-state protocol for data sharing. RRI-D is not validated for individual use, and no clinical or efficacy claim is made.

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1. Introduction: the limits of single-state metrics

A single resting value cannot distinguish a system that moves little from a system that moves a lot along one coupled axis. Resting RMSSD, SDNN or isolated coping scales summarize one state, and so they report magnitude at best.

Two properties of a regulatory system should be kept apart. Excursion is how far the system moves across states. Dimensionality is the number of independent directions in which it moves. A system can swing widely yet stay on a line, because all its variables are coupled, or it can move little while keeping a rich internal structure.

The same problem has been described outside HRV research. For mindfulness-based interventions, Demarzo^[1] argues that a static, linear dose–response model cannot explain the mixed evidence on home practice, and proposes that different dimensions of practice play different roles across phases of training, with recursive, non-linear and sometimes discontinuous change. A single magnitude, whether minutes of practice or resting RMSSD, cannot represent a process whose structure changes.

This paper builds on the view that reduced dimensionality of the response space is a measurable construct^{[2][3]}, which has since passed a first preregistered test^[4]. We do not re-derive that work. We ask what follows if the construct is taken seriously as a candidate marker: which predictions it makes about early change, about different kinds of intervention, and about the relation between physiological and psychological repertoire. We also ask what the published algorithm can and cannot deliver, and we answer the last question with a simulation rather than with assertion.

2. The Response Repertoire Index (RRI-D and RRI-R)

This paper uses RRI-D v1, the version fixed in a preregistration (OSF 10.17605/OSF.IO/G2EUW) and reported in a research note^[4]. Recordings cover K standardized states; the reference protocol has five (seated rest, mental arithmetic, recovery, standing, paced breathing at 6 breaths per minute). The steps are:

1. Per state, compute four features: ln RMSSD, ln LF power (0.04–0.15 Hz), mean RR and the Poincaré ratio SD1/SD2. HF is excluded because ln HF and ln RMSSD carry largely the same information^[3].
2. z-standardize each feature with the mean and SD of a reference sample (in current work, leave-one-participant-out estimates from the study sample), then centre each person's $K \times 4$ matrix on that

person's mean across states.

3. Compute the 4×4 covariance matrix of the centred matrix and its eigenvalues $\lambda_1 \geq \dots \geq \lambda_4$.
4. Excursion $E = \sum \lambda_i$. Dimensionality $RRI-D = (\sum \lambda_i)^2 / \sum \lambda_i^2$, the Hill number of order 2^[5]. RRI-D ranges from 1 (all reorganization along one axis) to $\min(4, K - 1)$.

Because standardization uses sample norms rather than each recording's own spread, excursion is preserved in the matrix and E and $RRI-D$ are computed from the same eigenvalues. R-R intervals must be of ECG quality; artefacts are corrected with an adaptive algorithm^[6], not with a fixed 20% rule.

Empirical status. In the preregistered test on open data from 41 healthy adults^[7], $RRI-D$ was computable in all participants, bootstrap reliability was 0.71, the median was 1.59 (IQR 1.42–1.80), and $RRI-D$ was unrelated to excursion ($\rho = -0.09$, 95% CI -0.37 to 0.20) and weakly related to resting $\ln RMSSD$ ($\rho = 0.21$). Individual 95% intervals had a median width of 0.67. A first test on WESAD failed its feasibility criterion because the fixed artefact rule rejected respiratory sinus arrhythmia during slow breathing^[4]. No reference sample and no test–retest data across days exist yet.

RRI-R. The psychological counterpart applies the same Hill-number logic to the profile of strategy use across the subscales of an established coping or regulation instrument, such as the Brief COPE or the CERQ, rather than to a new questionnaire^[3]. Symptom inventories are not suitable, because they profile distress rather than strategies. $RRI-R$ has not yet been tested empirically.

3. Positioning within resilience research

Resilience research increasingly treats resilience as a process. Kalisch and colleagues^[8] describe it as the maintenance of mental health despite adversity and argue that research should focus on the dynamic processes of adaptation, studied in prospective longitudinal designs. A single resting value is therefore a poor candidate for a resilience marker, and $RRI-D$ is not presented as resilience itself. We position it as a candidate marker of regulatory latitude, meaning the room a system has to reorganize across different demands, which may be one determinant of the adaptation process. Three bodies of work frame this.

Loss of complexity. Lipsitz and Goldberger^[9] hypothesized that age-related loss of physiologic complexity impairs adaptation to stress, and Manor and Lipsitz^[10] argue that such loss narrows the range of adaptive responses available. $RRI-D$ is a multivariate, between-state counterpart. Complexity measures describe the temporal structure of one signal, whereas $RRI-D$ describes how independent several channels are across controlled states.

Early-warning signals. Near a tipping point, recovery from small perturbations slows, and variance and autocorrelation rise^[11]. In mood data, van de Leemput et al.^[12] found that elevated autocorrelation, variance and correlation between emotions were related to the probability of a transition into or out of depression. Rising correlation between variables is exactly what lowers RRI-D in a multi-state matrix. H1 can therefore be read as a candidate response-space counterpart of critical slowing down. This link is a hypothesis and has not been shown for HRV features. The two approaches also use different axes: RRI-D is computed across controlled states within a session, early-warning indicators across time in spontaneous fluctuations. Early-warning signals are also known to need long, dense time series and to fail for some kinds of transition. H1 should therefore be tested together with classical indicators (variance and autocorrelation of within-state R-R series), and it would be weakened if those indicators explain the decline in D completely.

Regulatory flexibility. Bonanno and Burton^[13] propose three components of regulatory flexibility: context sensitivity, repertoire and response to feedback. RRI-R corresponds to the repertoire component only. The other two components are not captured, and any claim about psychological flexibility in this paper is limited accordingly.

The recovery state in the protocol gives a within-session measure of return toward baseline after a stressor state. H3 therefore uses recovery as an outcome alongside strain, which ties the framework to the process view. The term resilience is also used widely in commercial coaching and training. The competing-interests statement applies to this paper in particular.

4. Three hypotheses on systemic resilience

Each hypothesis is stated so that specific data could contradict it. Notation: D = RRI-D, E = excursion ($\Sigma\lambda$), M = resting RMSSD, R = RRI-R, S = a strain outcome (symptom or exhaustion score), Q = a recovery outcome (speed and completeness of return toward baseline after a stressor state).

H1 Early-warning decay

Under sustained load, D declines before resting vagal tone does. Formally, within persons across repeated sessions, the slope of D over time is negative while the change in M stays inside a preregistered equivalence margin. Lagged, D at session t predicts M at session t + Δ beyond M at t.

- Test: repeated multi-state sessions per person; per-person slopes of D, an equivalence test (two one-sided tests) for M against a margin fixed in advance, and a cross-lagged model of D and M. Classical early-warning indicators (variance and lag-1 autocorrelation of the within-state R-R series) are computed alongside (Section 3). Because change may be discontinuous rather than gradual^[1], a change-point model is fitted alongside the linear slope; H1 is also supported if a downward change point in D precedes any change point in M.
- Feasibility: with measurement error taken from Study 2, 36 persons and 5 sessions detect a mean decline of 0.1 RRI-D units with 84% power and a decline of 0.2 with near certainty (Section 5, Result 4). This assumes session-to-session error equals within-session bootstrap error, which is optimistic. Power was computed for the linear test only.
- Contradicted if M declines no later than D, if the decline in D is explained by falling signal-to-noise ratio (Section 5, Result 2), or if variance and autocorrelation explain it completely.
- Not testable with current open datasets, which are single-occasion. Section 7 states what is needed.

H2 Measurement dissociation by intervention class

Two classes of intervention differ in which quantity they shift. Class A acts on amplitude of autonomic response (for example aerobic conditioning). Class B acts on multi-state self-regulation (for example multi-state biofeedback). The prediction is a crossover interaction: $\Delta E(A) > \Delta E(B)$ and $\Delta D(B) > \Delta D(A)$.

- Test: trials with pre and post multi-state measurement, class assigned by mechanism before the trial, and a class $\times$ outcome interaction.
- Contradicted if both classes shift both outcomes equally, or if the pattern is reversed.
- This is a prediction about what the two measures distinguish. It makes no claim that any particular method works. Mindfulness-based interventions offer a natural test case: Demarzo^[1] distinguishes attentional, constructive and deconstructive families of practice as one source of heterogeneous outcomes. Whether these families shift E and D differently is an open, testable question, and it would show whether part of the mixed dose-response evidence reflects outcomes measured as a single-state magnitude.

H3 Cross-domain relation of D and R

We do not assume one functional form. Three models of strain are compared, and they predict different patterns.

Model	Form	Distinct prediction
Additive	$S = a - b_1D - b_2R$	Trade-off between D and R is constant at every level
Multiplicative	$S = a - b_3DR$	The effect of low D grows as R falls
Conjunctive threshold	S is high only if $D < \tau_D$ and $R < \tau_R$	Low D alone does not raise S while R is above τ_R

- Test: cross-validated comparison of the three models on data that contain both D and R, run separately for strain (S) and for recovery (Q) as outcomes. Because the additive model is nested in the multiplicative one, the additive model is retained unless the interaction model improves out-of-sample error by a preregistered margin.
- Sample size: at $N = 41$ none of the three forms is identified reliably (44–58% correct). An interaction of the assumed size is identified in 97% of samples at $N = 200$, and a threshold pattern in 82% at $N = 400$ (Section 5, Result 5).
- The claim that high R keeps function stable but uses up reserves over time is a separate longitudinal hypothesis and is not tested cross-sectionally.
- Contradicted if the additive model predicts out-of-sample at least as well as the two interaction models.

5. Simulation study: what RRI-D v1 can measure and what studies need

The simulations test what RRI-D v1 can measure and how large studies of H1 and H3 must be. They do not test the hypotheses, because each generative model contains its structure by design.

Model. Each simulated person has K states. A latent vector of r independent channels ($r = 1$ to 4) is mixed into the four features through a random orthonormal loading matrix, scaled by an amplitude parameter; independent noise (SD 0.15 or 0.30 in scaled units) and a person-specific baseline are added. Features are placed around a typical baseline (RMSSD 35 ms, LF 600 ms², mean RR 850 ms, SD1/SD2 0.35) using fixed physiological scales (0.5 and 0.7 log units, 100 ms, 0.1). Samples of 41 persons are standardized with leave-

one-out norms exactly as in Section 2. Seeds are fixed, and code and raw results are provided with the paper.

True channels r	$K = 5$ (mean $\pm$ SD)	$K = 8$	$K = 12$
1	1.17 $\pm$ 0.19	1.16 $\pm$ 0.13	1.15 $\pm$ 0.09
2	1.52 $\pm$ 0.28	1.69 $\pm$ 0.24	1.79 $\pm$ 0.20
3	1.82 $\pm$ 0.35	2.15 $\pm$ 0.33	2.38 $\pm$ 0.28
4	2.07 $\pm$ 0.37	2.56 $\pm$ 0.38	2.90 $\pm$ 0.35

Result 1. RRI-D orders true dimensionality at group level. Amplitude 1.0, noise 0.15, 4,100 simulated persons per cell.

With five states, values are compressed toward the lower bound and adjacent levels overlap by more than one SD. More states spread the scale. The observed Study 2 median of 1.59 lies between the $r = 2$ and $r = 3$ rows at $K = 5$; this is a plausibility check, not an estimate of channel count.

Result 2. Noise adds apparent dimensions at low signal-to-noise ratio. At $K = 5$ and $r = 1$, mean RRI-D falls from 1.75 to 1.05 as amplitude rises from 0.3 to 2.0 at fixed noise. At $r = 4$ it stays near 2.06 at all amplitudes. Low excursion relative to measurement noise therefore inflates RRI-D, which is consistent with the asymmetric bootstrap intervals reported for Study 2.

Result 3. The observed near-zero correlation with excursion is what independence plus noise predicts. In populations where true dimensionality and total excursion vary independently (r uniform 1–4, amplitude uniform 0.4–1.6), the median sample correlation $\rho(\text{RRI-D}, E)$ at $N = 41$ was -0.13 (90% range -0.39 to 0.14) at noise 0.15 and -0.26 at noise 0.30. The observed value of -0.09 fits the low-noise case. A small negative correlation in future data should not be read as a physiological trade-off without checking signal-to-noise.

Result 4. Power for H1. Using the Study 2 measurement SD (about 0.17, derived from the median interval width of 0.67) and between-person variation in slopes of 50% of the mean decline, power of a one-sided test on per-person slopes ($\alpha = 0.05$) was:

Persons	Sessions	Decline 0.1	Decline 0.2
20	5	0.64	0.98
36	3	0.77	> 0.99
36	5	0.84	> 0.99
36	8	0.93	> 0.99
60	5	0.97	> 0.99

The size of a real decline is unknown, and day-to-day error is likely larger than within-session error. The figures are therefore lower bounds on the sample needed.

Result 5. Distinguishing the H3 models needs large samples. Data were generated from each model (standardized D and R, residual SD 1; additive slopes -0.4 ; interaction $+0.35$; threshold jump 1.2 below -0.5 SD on both) and the model with the lowest 5-fold cross-validated error was selected. The correct model was chosen in 44–58% of samples at $N = 41$; at $N = 200$ the multiplicative model was identified in 97% and the threshold model in 60%; at $N = 400$ in 100% and 82%. A truly additive model was chosen in only about 60% at every N , because the nested interaction model fits equally well; hence the parsimony rule in H3.

6. Implications and limitations

The framework describes a person's response space on two axes: excursion E (how far the system moves) and dimensionality D (in how many independent directions). High E with low D describes strong swings along one coupled direction; high E with high D describes broad, structured reorganization. Low E is the least informative region, because noise inflates D there (Result 2); such values should be flagged rather than interpreted. This two-axis description is a research tool, not a diagnostic classification.

Three methodological recommendations follow.

- **Adaptive artefact handling.** A fixed 20% rule removed respiratory sinus arrhythmia during slow breathing and would have excluded the paced-breathing state in 59% of participants in Study 2^[4]. Adaptive algorithms should be used for any protocol with slow breathing.

- **Fixed protocol and reported K.** RRI-D depends on the number of states (Result 1). Values are comparable only within the same protocol.
- **Report E and signal quality with D.** RRI-D alone is not interpretable when excursion is small relative to measurement noise.

Limitations:

- The simulations assume a linear latent model with Gaussian noise. Real autonomic dynamics are nonlinear and non-stationary.
- Empirical evidence for RRI-D comes from one successful preregistered test in 41 healthy adults. There is no reference sample, no test-retest study across days, and no data from clinical groups.
- Individual precision is limited (median 95% interval width 0.67 on a scale of 1 to 4). RRI-D is suitable for group research, not for interpreting a single person's value.
- RRI-R has not been tested. H3 is therefore entirely prospective.
- Applications such as burnout prevention, trauma recovery or biofeedback personalization are research questions, not claims. Nothing in this paper is evidence for the efficacy of any coaching or therapeutic method.

7. A call for preregistered multi-state datasets

No open dataset we are aware of combines several standardized states, repeated sessions and a strain outcome. The following minimal protocol would allow all three hypotheses to be tested, and we invite groups with such data, or the means to collect them, to contact the author.

Element	Minimal specification	Serves
States	Seated rest, cognitive stress, recovery, posture change, paced breathing; order counterbalanced	H1, H2, H3
Number of states	At least 5; 8 or more preferred, since more states spread the scale and improve resolution (Section 5)	All
Duration per state	About 5 minutes, following short-term HRV convention	All
Sensor	Chest-strap ECG or ECG with R-peak detection; raw R-R intervals and artifact flags shared	All
Repeated sessions	Several sessions per person over weeks to months	H1
Intervention arms	Class A and class B assigned by mechanism, with pre and post sessions	H2
Psychological measures	A repertoire instrument (RRI-R) and a strain outcome	H3
Registration	Hypotheses, margins and analysis code preregistered before data are examined	All

Existing open datasets with several states, such as WESAD^[14] and the Sinichi et al.^[7] data, have already served to test measurability, but they are single-occasion and contain no psychological repertoire measure, so they cannot test H1 to H3.

Statements and Declarations

Funding

No specific funding was received for this work.

Potential Competing Interests

The author develops the Ultimate Code coaching method and the Code Connect and HRV Meister measurement software, in which RRI-D is implemented, and earns income from coaching, training and licensing. The term resilience is used in commercial coaching; this paper contains no evidence for the

efficacy of any method, product or intervention. The author has no relationship with sensor manufacturers.

Data Availability

No new empirical data were collected. The Python implementation of RRI-D v1 and all simulation scripts with seeds and raw outputs are available on OSF: <https://doi.org/10.17605/OSF.IO/CDKMW>. Empirical results cited are from the preregistered analyses at [doi:10.17605/OSF.IO/D8TKM](https://doi.org/10.17605/OSF.IO/D8TKM) and [doi:10.17605/OSF.IO/G2EUW](https://doi.org/10.17605/OSF.IO/G2EUW).

Use of Generative AI

Claude (Anthropic) was used to draft text and to write and run the simulation code. The author checked the content, the code and the references and takes full responsibility for them.

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Declarations

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Potential competing interests: The author develops and commercially offers the Ultimate Code coaching method and HRV measurement software in which the Response Repertoire Index (RRI-D) is implemented. He developed RRI-D and cites his own preprints. This work received no funding.