

Research Article

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

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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.

Key Terms

The following terms are used throughout. They are collected here so that the paper can serve as a common reference for the construct.

Term	Meaning in this paper
State	A standardized recording condition of fixed duration, for example seated rest or standing.
Feature	A summary number computed from the R-R series of one state. Four features are used (Section 2).
Excursion (E)	How far the system reorganizes across states, computed as the sum of the eigenvalues of the feature covariance matrix.
Dimensionality (RRI-D, D)	The effective number of independent directions of reorganization, computed as the Hill number of order 2 of the eigenvalues. It ranges from 1 to $\min(4, K - 1)$.
RRI-R (R)	The same Hill-number logic applied to the subscale profile of an established coping or regulation instrument. Not yet tested.
Regulatory latitude	The room a system has for reorganizing differently under different demands. A working concept that RRI-D is proposed to approximate, not a measured quantity.
Dimensional collapse	A persistent reduction in the effective dimensionality of the response space ^[2] . Used here as a descriptive hypothesis; no clinical condition is shown to involve it.

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.

Why these four features. The four features were chosen to carry different physiological information with as little overlap as possible. They are not meant to be exhaustive, and each is a descriptive summary of the R-R series rather than a direct measure of vagal or sympathetic activity.

Feature	What it mainly reflects	Why it is included	Main caveat	Sources
ln RMSSD	Beat-to-beat variability, mainly vagally mediated.	Standard short-term index of cardiac vagal modulation.	Strongly affected by breathing rate and depth.	[7] [8] [9]
ln LF power (0.04–0.15 Hz)	Slower oscillations linked to baroreflex activity and, during slow breathing, to respiration.	Captures regulation on a slower time scale than RMSSD.	Not a pure sympathetic index. It is largely shaped by parasympathetic activity and breathing.	[7] [10]
Mean RR	Average heart period, the net result of vagal and sympathetic influences on the heart.	The only feature that is a level rather than a variability, so it carries information that variability measures do not.	Also reflects non-autonomic influences such as intrinsic heart rate.	[7] [11]
SD1/SD2	Ratio of short-term to long-term variability in the Poincaré plot.	A shape measure rather than an amplitude: it changes when short- and long-term variability move differently.	SD1 is approximately proportional to RMSSD, and Poincaré descriptors largely re-express linear indices. Only the ratio is used for this reason.	[12] [8]

Expected independence. The four features are not expected to be statistically independent. RMSSD and

LF are both influenced by vagal activity and breathing, and SD1/SD2 is built from quantities related to RMSSD. RRI-D does not assume independence. It measures how many separate directions remain in the joint reorganization across states, and coupling between features concentrates variance in few eigenvalues and lowers D. Partial overlap therefore narrows the range of D but does not invalidate it. How strongly the features covary is an empirical question, and we give a first answer from open data. In an exploratory recomputation from the beat series of 37 of the 41 participants of Sinichi et al.^[13], with each person's z-standardized features centred across the five states, the four features were substantially coupled (table below).

Feature pair	Pooled within-person r	95% interval (participant bootstrap)
ln RMSSD and ln LF	0.76	0.70 to 0.82
ln RMSSD and mean RR	0.71	0.65 to 0.78
Mean RR and SD1/SD2	0.58	0.49 to 0.69
ln RMSSD and SD1/SD2	0.44	0.36 to 0.55
ln LF and mean RR	0.38	0.32 to 0.45
ln LF and SD1/SD2	-0.10	-0.23 to 0.06

Pooled over 37 persons $\times$ 5 states = 185 person-states. The first two principal axes of the pooled covariance carried 92% of the variance (58% and 34%), which corresponds to a pooled participation ratio of 2.2 (bootstrap 95% interval 1.9 to 2.3). For the same 37 persons the recomputation gave a median individual RRI-D of 1.56 (IQR 1.35–1.75, range 1.16–2.05), close to the registered value of 1.59 (IQR 1.42–1.80) in all 41 participants. The recomputation was not preregistered, follows the Welch and 4 Hz cubic-spline specification of Borschel^[3] for LF, but is not the registered implementation and uses a subset of the sample. It is therefore an illustration of the coupling, not a replacement for the registered values. A plausible reading is that the states mostly move the features along a small number of shared axes, for example states that raise heart rate also tend to lower beat-to-beat variability. This is also why values of RRI-D between 1 and 2.5 are typical and why no participant in the recomputation came close to the ceiling of 4.

Why four and not five or six. Three considerations led to four features. First, redundancy and interpretability: the obvious additions are either close to an included feature or hard to interpret in short recordings. HF power carries largely the same information as $\ln$ RMSSD ($r = 0.92$ in the simulated reference sample of Borschel^[3], and 0.91 across states in the recomputation above), and pNN50 is another time-domain index of beat-to-beat variability generally regarded as vagally mediated like RMSSD^{[7][8]} ($r = 0.88$ with $\ln$ RMSSD). Sample entropy was noise-dominated at segment lengths of 3 to 5 minutes^[3]. The LF/HF ratio has been challenged as an index of autonomic balance^{[14][10]}, and the Task Force^[7] cautioned against interpreting very-low-frequency power in short recordings. Second, a mathematical ceiling: the matrix centred across K states has rank at most $K - 1$, so with five states RRI-D cannot exceed 4 however many features are used (Section 2, step 4), and a fifth or sixth feature could not raise it. Simulation showed, however, that the ceiling was not the binding constraint. Feature independence was^[3]. With more states or longer segments, physiologically distinct additional features, for example from respiration or blood pressure, could raise the ceiling. They are not tested here. Third, the simulation work that preceded this paper compared feature sets directly. Removing $\ln$ HF and sample entropy from an initial six-feature set raised the separation between an intact and an excursion-matched phasic-collapse archetype from 0.47 to 0.79 RRI-D units, and the $\ln$ HF correlation alone reduced discrimination by roughly 40%^[3]. Four is therefore a pragmatic minimum for ECG-only data, not a claim that the autonomic system has four dimensions.

Why these five states. The five states were chosen because they load different regulatory mechanisms: a central cognitive demand, a postural and baroreflex demand, a respiratory-baroreflex demand, and recovery. This is a requirement of the construct. If all states challenged the same mechanism, no protocol could show more than one direction of reorganization. The states are common laboratory conditions in psychophysiology, and recommendations for planning such designs are summarized by Laborde et al.^[9]. Five is also the smallest number at which the ceiling $K - 1$ equals the number of features.

State	Demand	Direction typically reported at group level	Sources
Seated rest	Reference condition with spontaneous breathing.	Baseline against which reorganization in the other states is judged.	[7][9]
Mental arithmetic	Cognitive load, driven by central appraisal.	Lower high-frequency (vagally mediated) variability under mental stress.	[15][16]
Standing	Orthostatic challenge engaging the baroreflex.	Vagal withdrawal and sympathetic activation.	[7]
Paced breathing, 6 breaths per minute	Respiratory-baroreflex stimulation.	Respiratory sinus arrhythmia shifts into the LF band and baroreflex-related oscillation is engaged.	[17]
Seated recovery	Return after a stressor state.	Partial return toward baseline. Speed and completeness vary between persons.	[18][15]

The listed directions are typical group-level findings. Individual deviations from them are part of what RRI-D is meant to capture. The reference order in this section is not binding: Section 7 recommends counterbalancing.

Empirical status. In the preregistered test on open data from 41 healthy adults^[13], 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^[19] 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.

Why more independent directions might be advantageous. The central claim of this paper is that the number of independent directions in which the autonomic system reorganizes carries information that the amount of reorganization does not. Why should more directions be advantageous? We give four plausible arguments. They are arguments for a hypothesis, not findings, and the present empirical status of RRI-D (Section 2) supports none of them yet.

A simple contrast. Consider two people with the same total excursion across the five states. In person A every state moves the same coupled pattern: heart rate rises, vagally mediated variability falls in proportion, and the other features follow that single pattern. In person B the states reorganize the features differently. Mental load mainly lowers beat-to-beat variability, slow paced breathing mainly reshapes the slower oscillation, and standing changes heart period and variability in yet another combination. One number per state describes person A, and person B needs more. RRI-D is close to 1 for A and larger for B. Whether B's pattern is better for adaptation is the hypothesis, not a result.

1. **Coverage of demands.** Berntson et al.^[11] showed that modes of autonomic control do not lie on a single continuum from parasympathetic to sympathetic dominance but occupy a two-dimensional space. A given change in heart rate can therefore be produced by more than one combination of branch activity. A system that uses one route has fewer ways to meet a new demand than one that can use several. The same logic underlies Ashby's^[20] law of requisite variety, by which a regulator can absorb disturbances only if its own repertoire of responses is at least as varied as they are. We use the law as an analogy and do not claim that the autonomic system obeys it.
2. **Context-appropriate regulation.** The neurovisceral integration model^{[21][22]} proposes that prefrontal–limbic circuits adjust autonomic output to context in the service of self-regulation and adaptability, and it relates compromised inhibitory control to relatively fixed, disinhibited sympathetic activation, as in anxiety. If this is right, how differently the autonomic pattern looks

across demands should say something about regulatory quality beyond the level of vagal tone at rest. RRI-D is one way to quantify that context dependence across controlled states.

3. **Efficient turning on and off.** McEwen^[18] describes adaptation as depending on systems being turned on and off efficiently, and lists failure to shut off activity after stress and inadequate responses among the routes to allostatic load. A system with a wider repertoire may have more ways to leave an activated pattern. This is why recovery after a stressor state is used as an outcome in H3.
4. **Compensation.** If one regulatory route is impaired, a system that already uses other routes may compensate, whereas a system coupled along one axis has nothing to fall back on. This argument fits the loss-of-complexity view discussed below^{[23][24]} and accounts of psychological flexibility as the ability to adapt to varying demands, which is described as absent in many forms of psychopathology^[25]. It has the least direct physiological support of the four.

Limits of the argument. More dimensions are not unconditionally better. Uncorrelated noise also raises RRI-D (Result 2), and a system could be erratic rather than flexible. The hypothesis concerns structured, state-dependent reorganization that is reproducible across sessions. This is why E and signal quality are reported with D (Section 6) and why test–retest data are needed.

Three bodies of work place the construct in the resilience literature.

Loss of complexity. Lipsitz and Goldberger^[23] hypothesized that age-related loss of physiologic complexity impairs adaptation to stress, and Manor and Lipsitz^[24] 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^[26]. In mood data, van de Leemput et al.^[27] 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^[28] 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). Each hypothesis is introduced with the gap it addresses and the reason it was chosen. The section closes with how the three relate.

H1. Early-warning decay

Background. Resting vagal measures are the usual physiological readout of load, and they relate to strain cross-sectionally, for example to exhaustion in a large population sample^[29]. It is unknown whether the multi-state structure of the response changes before the resting value does. This is the question on which a dimensionality measure would add most if it held, because a change that precedes the resting value would be informative for monitoring, and it can be tested directly with repeated sessions. It is also the hypothesis for which the early-warning literature offers a formal analogy (Section 3). H1 is often discussed informally in the context of burnout. It is stated here for sustained load in general and makes no claim about burnout as a condition or about prevention.

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 $t + \Delta$ 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

Background. Interventions are usually compared on a single physiological outcome, typically resting HRV. A single outcome cannot show whether an intervention made the system move more (excursion) or in more ways (dimensionality). Before asking whether any method works, one has to know whether E and D can be told apart in intervention data. A crossover pattern across two classes defined by mechanism is the simplest design that can show this, and it needs only pre and post multi-state sessions. A failure of H2 would also be informative: it would suggest that D adds little beyond E.

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

Background. Physiological and psychological regulation are mostly studied in separate literatures. Coping and emotion-regulation strategies are related to psychopathology one strategy at a time (for example [30]), and psychological flexibility is described as a core feature of health[25], but a joint description of physiological and psychological repertoire is missing. RRI-R applies the same Hill-number logic to established instruments, so both domains can be put on one scale without a new questionnaire. Three functional forms are compared because theory does not say which is right: whether the two repertoires trade off at a constant rate (additive), whether low D matters more as R falls (multiplicative), or whether strain is raised only when both are low (threshold).

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.

How the three hypotheses relate

The hypotheses are logically independent: each can be supported or contradicted without the others. They are nevertheless complementary, because each tests a different property that a candidate marker needs, along a different axis of comparison.

Hypothesis	Question about RRI-D	Axis of comparison	Data needed	A negative result would suggest
H1	Does it change when it should?	Within persons, across time	Repeated multi-state sessions	D carries no early information beyond M and classical indicators.
H2	Does it differ from what is already measured?	Between measures, across intervention classes	Pre and post multi-state sessions in two classes	D adds nothing beyond E.
H3	Does it relate to something beyond physiology?	Between domains, across persons	Multi-state sessions plus RRI-R and strain and recovery outcomes	D and R relate to strain and recovery in none of the three forms.

Evidential dependencies run in one direction. If H2 failed, so that D carried no information beyond E, results for H1 and H3 could no longer be read as being about dimensionality. If H1 failed, H2 and H3 would still stand as statements about measurement and about cross-domain structure. One dataset built to the minimal protocol in Section 7 can test all three, which is why the protocol is proposed as a whole.

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.

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

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

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.
- The rationale in Sections 2 and 3 consists of plausibility arguments and of literature on the individual features and states. It is not evidence that a higher RRI-D is advantageous.
- The four features are partly coupled. In an exploratory recomputation on 37 participants the pooled within-person correlations ranged from -0.10 to 0.76, and at five states the ceiling of RRI-D is 4 irrespective of the number of features. A preregistered report of the correlation structure in a full sample is still needed.

- 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
Feature reporting	Across-state correlation matrix of the four features, the cognitive task used, and signal quality for each state	All
Registration	Hypotheses, margins and analysis code preregistered before data are examined	All

Existing open datasets with several states, such as WESAD^[31] and the Sinichi et al.^[13] 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.

Appendix A. Summary of changes in version 2

Version 2 responds to a public review of version 1. No result, simulation, hypothesis or limitation of version 1 was removed or changed. The changes are additions that explain concepts and methodological choices, plus one exploratory recomputation (labelled as such) that quantifies the coupling between features.

Review point	Change	Where
1. Describe the three hypotheses	A background paragraph for H1, H2 and H3 states the gap each addresses and why it was chosen.	Section 4
2. Why more independent dimensions might be advantageous	New block with a contrast between a coupled and a differentiated response pattern, four plausible arguments with sources, and the limits of the argument.	Section 3
3. Why these four HRV features	Table of what each feature contributes, with sources and caveats; discussion of expected independence; reasons for four and not five or six.	Section 2
4. Why these physiological states	Table of the five states, the demand each places on regulation and the typical direction reported, with sources.	Section 2
5. How the hypotheses complement one another	New subsection with a comparison table and a note on evidential dependencies.	Section 4
Additional	Key terms table; exploratory recomputation of the feature correlations from open data; two limitations; one added item in the minimal protocol; acknowledgement; 17 added references.	Sections 1, 6, 7; Declarations; References

Statements and Declarations

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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 and Code 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 and doi:10.17605/OSF.IO/G2EUW. The exploratory recomputation of feature correlations in Section 2 uses beat series that the author derived from the openly available data of Sinichi et al.^[13] (<https://osf.io/y2q3r>, CC-BY 4.0); the script and the derived feature table are available at <https://doi.org/10.17605/OSF.IO/G2EUW> (folder `feature_correlation_v2`). They were added after the registration and are not part of the preregistered analysis.

Use of Generative AI

Claude (Anthropic) was used to draft and revise 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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