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UNCOVERING LATENT STRESS DIMENSIONS IN UNIVERSITY STUDENTS: A PCA SIMULATION STUDY WITH SENSITIVITY ANALYSIS AND THE DYNAMIC STRESS SIGNATURE FRAMEWORK

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ABSTRACT

Academic stress and burnout in university students manifest through multiple interrelated behavioral, cognitive, and physiological channels whose co-variation structure is routinely discarded by conventional statistical analysis. This simulation study applies principal component analysis (PCA) to a synthetic eight-variable behavioral dataset generated from a three-factor latent structure representing academic burnout — Academic Pressure, Psychological Depletion, and Performance Dread — and demonstrates that PCA recovers this structure with high fidelity while delivering measurable predictive advantages over raw-variable regression. The base scenario ($n = 237$) recovers the three-component structure explaining 86.8% of total variance, reduces mean variance inflation factor from 4.1 to 1.0, and achieves an AIC improvement of 21.6 units over conventional regression. A systematic sensitivity analysis across eight sample sizes ($n = 40$ to 400) and seven inter-variable correlation levels shows that Tucker's congruence coefficient reaches $\varphi \geq 0.95$ reliably at $n \geq 200$, and that PCA's AIC advantage persists across all correlation conditions tested ($\Delta AIC = 14.7$ to 17.1). At very small samples ($n = 40$), component recovery degrades substantially (mean $\varphi = 0.87$, stable solutions in only 36% of replications), establishing a practical lower bound on the method's applicability. Beyond the cross-sectional findings, this paper introduces the dynamic stress signature: each student's characteristic temporal sequence of dominant components across the academic calendar, individually unique and recoverable by longitudinal

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PCA, analogous to a stress fingerprint. The simulation design, sensitivity boundaries, and longitudinal framework together constitute a complete methodological guide for applied burnout researchers intending to deploy PCA in behavioral datasets.

Keywords: principal component analysis, simulation study, academic burnout, dynamic stress signature, sensitivity analysis, Tucker congruence, parallel analysis, Varimax rotation, multicollinearity, longitudinal PCA

1. Introduction

Academic stress and burnout among university students involve multiple co-varying behavioral and psychological indicators: workload pressure, emotional exhaustion, cognitive fatigue, sleep disruption, reduced self-efficacy, and evaluative anxiety move together in ways that individual-variable analysis misses. This co-variation is not noise. It reflects genuine shared causal processes — the same examination-period stressor produces simultaneous escalation in time pressure, cognitive load, and performance fear. Standard regression, which treats these indicators as independent additive predictors, recovers only a fraction of the available information and produces structurally unreliable estimates when predictors correlate substantially.

Principal component analysis (PCA) transforms correlated predictors into orthogonal components that each capture a distinct axis of the joint variation. The components are not measured variables — they are empirically discovered gradients, the directions along which students differ most. In a burnout dataset, one component might represent the demand-overload axis, another the resource-depletion axis, a third the evaluative-threat axis. These correspond to theoretically motivated burnout dimensions, but PCA finds them without presupposing their existence or composition.

This paper reports a simulation study that demonstrates the PCA pipeline on a synthetic eight-variable burnout dataset with known three-factor latent structure, then systematically quantifies how PCA performance changes as sample size and inter-variable correlation vary. The simulation approach serves two purposes. First, it provides ground truth: because the true component structure is known by design, the accuracy of recovery — measured by Tucker's congruence coefficient — can be

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assessed precisely. Second, it enables sensitivity analysis across conditions that a single empirical dataset cannot provide: the researcher can vary n from 40 to 400 and correlation strength from weak to extreme and measure exactly where the method becomes unreliable.

Beyond the cross-sectional demonstration, this paper introduces the dynamic stress signature — the concept that each student's burnout state follows a characteristic temporal trajectory across the academic calendar, and that longitudinal PCA applied at multiple time points recovers this trajectory as an individually unique, clinically actionable signature. The cross-sectional simulation establishes the component structure that forms the vocabulary of this signature; the longitudinal design is proposed as the direct next study.

Section 2 reviews the burnout literature and the theoretical basis of the dynamic stress signature. Section 3 describes the simulation design and analysis protocol. Section 4 presents base scenario results. Section 5 reports the sensitivity analyses. Section 6 develops the longitudinal extension. Section 7 discusses implications and limitations. Section 8 concludes.

2. Background

2.1 Academic Burnout: Dimensions and Measurement

Maslach and Leiter (1997) define burnout through exhaustion, cynicism, and reduced efficacy. Schaufeli, Martinez, Pinto, Salanova, and Bakker (2002) adapted this framework for students in the Maslach Burnout Inventory — Student Survey (MBI-SS), identifying emotional exhaustion, cynicism toward academic work, and reduced academic efficacy as the primary student burnout dimensions. Empirical studies consistently find substantial correlations among these dimensions and their antecedent stress variables: exhaustion correlates negatively with efficacy ($r = -0.41$ to -0.61), and both correlate with academic performance anxiety, sleep disruption, and time pressure (Salmela-Aro, Kiuru, Leskinen, & Nurmi, 2009). These correlations create multicollinearity in standard regression analyses of burnout predictors, a problem documented but rarely resolved in the literature (Dyrbye, Thomas, & Shanafelt, 2006).

2.2 PCA in Stress Research: What Is Known

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Leiter and Maslach (2004) used exploratory factor analysis to validate the six-area model of person-job fit in burnout, recovering three factors explaining 68% of variance. Salmela-Aro et al. (2009) applied PCA to a 16-variable academic demands dataset, finding that four components predicted dropout intention more accurately than individual variables. Neither study quantified PCA's advantage over raw-variable regression systematically, nor provided sensitivity bounds on component recovery. This simulation fills that gap.

2.3 Why PCA, Not Exploratory Factor Analysis

PCA and exploratory factor analysis (EFA) differ in a way that matters for the prediction objective of this study. EFA models the common variance among variables through latent factors, estimating unique variance for each variable separately. PCA redistributes all variance — common and unique — into components, treating the data geometrically. For the purpose of constructing orthogonal predictors that maximize explained variance in a criterion, PCA is the appropriate choice: its components are guaranteed orthogonal and account for all variance in the predictor set. EFA factors carry residual unique variances that reintroduce redundancy. PCA components are also fully reproducible: any researcher with the loading matrix can compute the same scores from new data by projection, without refitting.

2.4 The Dynamic Stress Signature

Standard burnout research treats the burnout state as a cross-sectional snapshot. This assumption discards temporal structure that carries clinical information. A student at week two of the semester presents a different stress profile than the same student at week fifteen. The dominant component — the dimension most strongly characterizing that student's current state — shifts across the academic calendar. One student escalates from Academic Pressure dominance at week two to Psychological Depletion dominance at week fifteen. Another student shows persistent Performance Dread throughout, with no Pressure escalation. Their total burnout scores at week fifteen may be identical; their trajectories are not.

This temporal pattern has a precise mathematical formulation. Suppose the eight stress variables are measured at T time points for each student. At each

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occasion t, PCA component scores are computed by projecting the student's data onto the loading matrix estimated from the full baseline sample. The dominant component at occasion t is the component with the highest absolute standardized score. The sequence of dominant components across t = 1, ..., T is that student's dynamic stress signature — a trajectory through component space that characterizes the temporal unfolding of their burnout state.

Two properties make the signature clinically useful. First, it is individually unique: two students with identical mean burnout severity can follow entirely different trajectories. Standard statistics cannot distinguish them; longitudinal PCA can. Second, it is predictively informative: a student whose signature shows early-onset Psychological Depletion — resource exhaustion appearing before the examination peak — is at higher cumulative burnout risk than a student whose Depletion component activates only at the peak. The signature identifies this vulnerability weeks before aggregate scores reach actionable thresholds.

The dynamic stress signature concept draws on an analogy from integrative clinical practice in which each individual presents not a fixed diagnosis but a shifting pattern of dominant states, and the practitioner tracks the current leading state to determine the appropriate intervention.1 The parallel to longitudinal PCA is direct: no two students share the same component trajectory over time, just as no two individuals share the same sequence of dominant states across life circumstances. The signature is individual, temporal, and actionable.

3. Simulation Design

3.1 True Latent Structure

The simulation embeds a known three-factor latent structure corresponding to three theoretically motivated burnout dimensions. The true loading matrix L specifies how eight behavioral variables — Academic Stress (AS), Emotional Exhaustion (EE), Cognitive Fatigue (CF), Sleep Disruption (SD), Self-Efficacy (SE), Time Pressure (TP), Social Withdrawal (SW), and Performance Anxiety (PA) — relate to three latent components. Table 1 presents L.

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Variable	C1 Academic Pressure	C2 Psychological Depletion	C3 Performance Dread
Academic stress (AS)	0.82	0.38	0.31
Emotional exhaustion (EE)	0.35	0.85	0.28
Cognitive fatigue (CF)	0.31	0.80	0.29
Sleep disruption (SD)	0.22	0.73	0.21
Self-efficacy (SE)	−0.29	−0.28	−0.79
Time pressure (TP)	0.84	0.30	0.27
Social withdrawal (SW)	0.24	0.69	0.28
Performance anxiety (PA)	0.30	0.28	0.87

Table 1. True loading matrix L used to generate the simulation population. Cross-loadings are included at realistic levels to reproduce the overlapping variance structure of burnout instruments. C1 = Academic Pressure, C2 = Psychological Depletion, C3 = Performance Dread.

The true population covariance matrix is $\Sigma = LL' + \Psi$, where $\Psi = \text{diag}(\psi_1, \ldots, \psi_8)$ contains unique variances computed as $\psi_j = \max(0.04, 1 - ||L_j||^2)$. The population correlation matrix is obtained by standardizing Σ. Cross-loadings are set at realistic levels (0.21 to 0.38) to reproduce the overlapping variance structure of burnout instruments — a cleaner loading matrix would understate the multicollinearity challenge that applied researchers face.

3.2 Data Generation

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For each replication, n observations are drawn from a multivariate normal distribution with the population correlation matrix: X = ZL_chol', where Z ~ N(0, I) and L_chol is the Cholesky factor of the correlation matrix. All variables are standardized to unit variance after generation. The outcome variable y is constructed as a weighted sum of the true component scores plus Gaussian noise: $y = 0.55f_1 + 0.45f_2 + 0.35f_3 + \varepsilon$, where $\varepsilon \sim N(0, 0.45^2)$ and f_1, f_2, f_3 are the scores on the three true components. This construction ensures that all three components predict y, so a regression model that recovers all three components outperforms one that does not.

All simulations used Python 3.11 with NumPy 1.26 and scikit-learn 1.4, with random seed fixed at 99 for the base scenario and varied across sensitivity replications.

3.3 Analysis Pipeline

Component retention

Parallel analysis (Horn, 1965) with 500 permutation datasets determined the number of components to retain. A component was retained when its real eigenvalue exceeded the 95th percentile of the permuted eigenvalue distribution for that component rank. This criterion outperforms the Kaiser eigenvalue-greater-than-one rule in simulation studies by Zwick and Velicer (1986).

Extraction and rotation

PCA extracted components from the standardized correlation matrix of X. Retained components received Varimax rotation. All downstream regression models used three components regardless of what parallel analysis retained in individual replications, to allow fair comparison across conditions.

Benchmark comparison

Two regression models predicted y. Model A used the eight raw standardized variables. Model B used the three PCA component scores. Both models underwent 10-fold cross-validation (5-fold for $n < 100$). Primary metrics were cross-validated MSE, R^2, and AIC. Mean VIF was computed for both predictor sets.

Component recovery

Tucker's congruence coefficient φ measured how well each simulation replication

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recovered the true loading matrix. A reference loading matrix was estimated from a large sample (n = 5,000). For each replication, φ was computed between the replication's loading matrix and the reference. A solution was classified as stable when $\varphi \geq 0.95$ (Lorenzo-Seva & ten Berge, 2006).

3.4 Sensitivity Conditions

Sensitivity Table 1 varied sample size across eight levels: $n \in \{40, 80, 120, 160, 200, 237, 320, 400\}$, holding the full population correlation structure fixed. Sensitivity Table 2 varied inter-variable correlation strength by scaling the off-diagonal elements of the population correlation matrix by a factor $s \in \{0.25, 0.40, 0.55, 0.70, 0.85, 1.00, 1.15\}$, holding n = 237 fixed. Each condition used 30 replications. The Tucker congruence table used 100 replications per sample size level.

4. Base Scenario Results (n = 237)

4.1 Component Structure

Parallel analysis retained one dominant component in the base scenario — a consequence of the high cross-loadings in the true L, which concentrate variance on the first component. Three components were retained for analysis as specified by the known ground truth. The three-component solution explained 86.8% of total variance. The Varimax-rotated loading matrix closely reproduced the true structure in Table 1, with marker variables ($|\text{loading}| \geq 0.50$) correctly assigned to their true component in all three cases.

Component 1 (Academic Pressure) showed highest loadings on AS and TP. Component 2 (Psychological Depletion) showed highest loadings on EE, CF, SD, and SW. Component 3 (Performance Dread) showed highest loadings on PA and SE (negative). No variable showed a cross-loading above |0.38| on a non-dominant component, satisfying the simple structure criterion at the |0.40| threshold (Tabachnick & Fidell, 2019).

4.2 Multicollinearity and Predictive Comparison

Mean VIF across the eight raw predictors was 4.1 (max 6.2). All three PCA component scores produced VIF = 1.0, confirming complete multicollinearity elimination. Table 2 summarizes the predictive model comparison.

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Model	Predictors (k)	CV MSE	R^2	AIC	ΔAIC vs Model B
Model A — raw variables	8	0.213	0.88	322.2	+21.6
Model B — PCA components	3	0.203	0.88	300.6	0 (reference)

Table 2. Base scenario predictive comparison (n = 237, 10-fold cross-validation). CV MSE = cross-validated mean squared error. AIC computed from cross-validated residuals. ΔAIC = 21.6 exceeds the decisive threshold of 10 (Burnham & Anderson, 2002). Model B achieves equivalent R^2 with five fewer parameters.

MSE improved by 4.8% from Model A to Model B. R^2 held constant at 0.88. The AIC improvement of 21.6 units reflects two separable contributions: five fewer parameters account for 10 AIC units; the remaining 11.6 units reflect genuine fit improvement from multicollinearity elimination. Tucker's congruence coefficient between the recovered and reference loading matrices was $\varphi = 0.977$, indicating excellent component recovery (threshold: $\varphi \geq 0.95$).

5. Sensitivity Analysis

5.1 Effect of Sample Size

Table 3 reports mean results across 30 replications at each sample size, holding the full correlation structure fixed. Three findings stand out.

n	VarExp%	VIF mean	MSE raw	MSE PCA	MSE red%	R^2 raw	R^2 PCA	ΔAIC	Tucker φ	n_comp
40	87.9	5.2	0.283	0.227	19.9	0.66	0.70	18.3	0.890	1.1
80	87.7	4.7	0.241	0.222	7.7	0.83	0.84	16.3	0.953	1.0
120	87.3	4.6	0.223	0.210	5.6	0.86	0.87	16.6	0.956	1.0

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160	87.5	4.4	0.218	0.210	3.4	0.88	0.88	15.5	0.967	1.0
200	87.2	4.3	0.208	0.202	2.8	0.89	0.89	15.8	0.944	1.0
237	87.7	4.4	0.215	0.209	2.6	0.88	0.89	16.2	0.981	1.0
320	87.5	4.4	0.209	0.205	2.1	0.89	0.90	16.7	0.986	1.0
400	87.3	4.3	0.205	0.202	1.6	0.90	0.90	16.2	0.982	1.0

Table 3. Sensitivity to sample size (30 replications per condition, full correlation structure). VarExp% = variance explained by three components; VIF mean = mean variance inflation factor across 8 raw predictors; MSE red% = percentage reduction in cross-validated MSE from Model A to Model B; Tucker φ = mean congruence coefficient against reference loading matrix; n_comp = mean number of components retained by parallel analysis.

First, Tucker's congruence rises sharply between n = 40 (φ = 0.890) and n = 80 (φ = 0.953), crossing the stability threshold of φ = 0.95 at approximately n = 80 and remaining stable above n = 200. This establishes n = 80 as the practical minimum for reliable component recovery and n = 200 as the threshold for consistent stability.

Second, MSE reduction is largest at small n: the raw-variable model suffers most from multicollinearity instability when n is small relative to p. At n = 40, PCA reduces MSE by 19.9%; at n = 400, the reduction is 1.6%. This pattern reflects the well-known sensitivity of ordinary least squares to multicollinearity at low degrees of freedom — PCA's advantage is greatest precisely where raw-variable regression is most unreliable.

Third, the AIC advantage of Model B is consistent across all sample sizes (ΔAIC = 15.5 to 18.3), confirming that the parsimony gain from reducing eight correlated predictors to three orthogonal components holds regardless of n. The AIC criterion does not depend on sample size in the way MSE does; it penalizes parameter count directly and rewards the simpler model consistently.

5.2 Effect of Inter-Variable Correlation Strength

Table 4 reports mean results across 30 replications at each correlation scaling level,

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holding n = 237 fixed. The scaling factor s multiplies the off-diagonal elements of the population correlation matrix, where s = 1.0 corresponds to the base scenario.

Scale s	Mean |r|	VarExp%	VIF mean	MSE raw	MSE PCA	MSE red%	R^2 raw	R^2 PCA	ΔAIC
0.25	0.15	51.9	1.1	0.208	0.203	2.5	0.81	0.81	15.9
0.40	0.25	58.9	1.3	0.212	0.208	2.0	0.83	0.83	14.7
0.55	0.34	65.9	1.5	0.208	0.203	2.4	0.85	0.85	15.8
0.70	0.43	72.5	1.8	0.212	0.207	2.3	0.86	0.86	15.6
0.85	0.52	80.2	2.5	0.206	0.200	3.0	0.88	0.88	17.1
1.00	0.61	87.4	4.3	0.214	0.209	2.3	0.88	0.89	15.6
1.15	0.69	93.3	1324.0	0.207	0.201	2.6	0.90	0.90	16.3

Table 4. Sensitivity to inter-variable correlation strength (30 replications per condition, n = 237). Scale s = off-diagonal scaling factor applied to the population correlation matrix. Mean |r| = mean absolute pairwise correlation among the 8 variables. VIF mean rises sharply above s = 1.0; at s = 1.15 (mean |r| = 0.69), the raw-variable predictor set is near-collinear (mean VIF = 1,324) while PCA component VIF remains 1.0 throughout.

Four findings emerge from Table 4. First, variance explained by three components increases monotonically with correlation strength, from 51.9% at s = 0.25 to 93.3% at s = 1.15. At low correlation (mean |r| = 0.15), the three components account for little more than half the total variance — the latent structure is too diffuse for PCA to compress efficiently. At high correlation (mean |r| = 0.69), the three components account for nearly all variance, reflecting the near-redundancy of the eight variables.

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Second, mean VIF for the raw predictor set escalates rapidly above s = 1.0: from 4.3 at s = 1.00 to 1,324 at s = 1.15. This near-singularity makes raw-variable regression numerically unreliable at high correlation. PCA component VIF remains exactly 1.0 at all levels, because orthogonality is a property of the transformation, not of the data.

Third, MSE reduction is modest but consistent across all correlation levels (2.0% to 3.0%), with no strong relationship to correlation strength. The AIC advantage, however, is stable across all conditions (ΔAIC = 14.7 to 17.1) — the parsimony gain from five fewer parameters holds regardless of correlation structure.

Fourth, the result at s = 0.25 (mean |r| = 0.15) is informative about PCA's lower bound. When variables barely correlate, PCA's three components still explain only 51.9% of variance, and MSE reduction is 2.5% — comparable to the high-correlation condition. This result confirms that PCA's predictive advantage is not primarily correlation-driven; it derives from the parsimony gain. However, the scientific value of the extracted components — their interpretability and theoretical coherence — diminishes sharply when variables do not substantially correlate. Applied researchers should not apply PCA when mean |r| falls below approximately 0.30.

5.3 Component Recovery: Tucker's Congruence

Table 5 summarizes Tucker's congruence coefficient across 100 replications per sample size. The stability threshold φ ≥ 0.95 (Lorenzo-Seva & ten Berge, 2006) marks reliable recovery.

n	Mean φ	Min φ	φ ⩾ 0.95 (%)	φ ⩾ 0.85 (%)
40	0.873	0.348	36.0	74.0
80	0.934	0.343	66.0	88.0
120	0.959	0.595	76.0	96.0
160	0.971	0.717	88.0	96.0
200	0.980	0.846	94.0	99.0

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237	0.977	0.865	86.0	100.0
320	0.988	0.901	97.0	100.0

Table 5. Tucker's congruence coefficient between recovered and reference (n = 5,000) loading matrices, across 100 replications per sample size. φ ≥ 0.95 indicates a stable, interpretable solution (Lorenzo-Seva & ten Berge, 2006). φ ≥ 0.85 indicates an acceptable solution with minor instability.

At n = 40, only 36% of replications achieve φ ≥ 0.95, and the minimum φ across 100 replications is 0.348 — a severely distorted solution. At n = 80, 66% achieve φ ≥ 0.95, and 88% achieve φ ≥ 0.85. The probability of a stable solution reaches 94% at n = 200 and 97% at n = 320.

These thresholds carry a direct practical implication. A researcher collecting data for a PCA study of academic burnout with eight variables should target n ≥ 200 to achieve a 94% probability of recovering a stable, interpretable component structure. At n = 120, the researcher has a 76% chance of stability — acceptable when data collection is genuinely constrained, but with explicit acknowledgment that one in four samples will produce a distorted solution. Studies with n < 80 should not apply PCA to this variable set.

6. The Dynamic Stress Signature: Longitudinal Extension

6.1 From Cross-Sectional Components to Temporal Trajectories

The three components established in Sections 4 and 5 — Academic Pressure, Psychological Depletion, and Performance Dread — define a three-dimensional space within which any student's stress state at any time point can be located. At a given time point, a student occupies a specific position in this space, described by three component scores (z_1, z_2, z_3). The dominant component is the component with the highest absolute standardized score at that time point: D(t) = argmax_j |z_j(t)|.

The dynamic stress signature is the sequence D = (D(1), D(2), ..., D(T)) across T measurement occasions. Two students with the same total burnout score at time T may have arrived at that score by entirely different paths. Student A: D = (Pressure, Pressure, Depletion, Depletion) — demand escalation followed by resource collapse. Student B: D = (Dread, Dread, Dread, Dread) — persistent

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evaluative fear without demand escalation or depletion. Standard cross-sectional analysis at time T cannot distinguish them. The signature distinguishes them at time 1.

6.2 Proposed Longitudinal Design

The proposed study measures the same eight-variable battery at T = 3 time points within a single academic semester: pre-semester (week 1), mid-semester (week 8), and examination period (week 15). Component scores at each time point are computed by projecting each student's standardized variable vector onto the reference loading matrix estimated from the baseline sample — a procedure known as score projection that preserves the comparability of scores across time points without refitting PCA at each occasion.

For each student at each time point, the dominant component D(t) is identified. The three-occasion signature D = (D(1), D(2), D(3)) is categorical, taking values in $\{P, L, R\}^3 = 27$ possible signature types, where P = Academic Pressure, L = Psychological Depletion, R = Performance Dread. Applied researchers may collapse rare types or treat the dominant component scores as continuous trajectories rather than categorical sequences, depending on sample size.

The primary hypothesis is that signature type at week 1 predicts burnout severity at week 15 beyond what total stress score at week 1 predicts — that is, the trajectory carries information above and beyond the level. A student with early-onset Depletion dominance (D(1) = L) is expected to show higher week-15 burnout than a student with D(1) = P, even when week-1 total scores are matched, because Depletion reflects resource exhaustion that compounds over the semester while Pressure can be intermittent.

6.3 Institutional Application

The practical utility of the signature for university wellbeing programs is direct. A student whose week-1 signature shows Depletion dominance requires recovery-oriented intervention — sleep hygiene, reduced cognitive load, counseling — at week 1, before the examination period makes the intervention harder to deliver and harder for the student to use. A student with Dread dominance requires self-efficacy development and assessment anxiety management. A student with Pressure

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dominance requires workload regulation and time management support.

At the institutional level, the distribution of signature types across a cohort characterizes the stress ecology of the university at a given academic period. If year-on-year tracking shows an increasing proportion of early-Depletion signatures, the institution faces a resource-exhaustion problem: students are depleting before examinations begin. If Performance Dread signatures increase, the assessment regime may be concentrating evaluative pressure in ways that require structural intervention. The signature provides both a screening tool for individual triage and a population-level indicator for institutional monitoring.

7. Discussion

7.1 What the Simulation Demonstrates

The simulation establishes three findings with direct practical implications. First, PCA recovers the true three-component burnout structure with high fidelity at $n \geq 200$ ($\varphi \geq 0.95$ in 94% of replications) but degrades substantially at $n \leq 40$ ($\varphi \geq 0.95$ in only 36% of replications). The $n \geq 200$ threshold is higher than the commonly cited $n \geq 5p$ rule ($n \geq 40$ for eight variables) and lower than the $n \geq 10p$ rule ($n \geq 80$ for eight variables). Applied researchers should treat $n = 200$ as the practical target and $n = 80$ as the minimum acceptable.

Second, PCA's AIC advantage over raw-variable regression is stable across all sample sizes and correlation levels tested (ΔAIC = 14.7 to 18.3). This advantage does not depend on severe multicollinearity: even at low correlations (mean $|r| = 0.15$, mean VIF = 1.1), Model B outperforms Model A by ΔAIC = 15.9. The parsimony gain — five fewer parameters — is the dominant contributor to the AIC improvement. This finding implies that PCA's model-selection advantage holds whenever the true predictor structure is lower-dimensional than the observed variable set, regardless of correlation level.

Third, the MSE reduction is largest at small n (19.9% at $n = 40$) and declines to negligible levels at large n (1.6% at $n = 400$). This pattern reflects a known property of multicollinearity: its damage to OLS coefficient stability is worst at low degrees of freedom. Applied researchers working with small samples — the common situation in clinical or institutional studies — stand to gain most from PCA

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preprocessing in predictive models.

7.2 Limitations of the Simulation Approach

Three limitations qualify the simulation findings. First, the simulation assumes multivariate normality throughout. Real burnout data carries ceiling effects, skewness, and ordinal scale constraints that violate this assumption. Robustness of PCA under non-normality has been documented in prior simulation work (Foldnes & Olsson, 2016), but the specific sensitivity boundaries in Tables 3 and 5 may not transfer directly to non-normal data. Future simulation work should vary the distributional assumptions.

Second, the true factor structure is fixed at three components. Real burnout data may have two, four, or more latent dimensions. The sensitivity of Tucker's congruence boundaries to the number of true components is not examined here. Researchers applying PCA to datasets with unknown true dimensionality face additional uncertainty beyond what the sensitivity tables quantify.

Third, the simulation uses a balanced component structure — all three components explain substantial variance. When one true component dominates (as in g-factor models of intelligence), PCA tends to recover the dominant component reliably regardless of sample size, but subsidiary components become unstable at lower n. Applied burnout researchers whose populations show one dominant stress dimension should treat the n = 200 stability threshold as conservative — their practical minimum may be lower for the dominant component but higher for subsidiary ones.

8. Conclusion

This simulation study demonstrated PCA's application to an eight-variable academic burnout dataset with known three-factor structure, systematically quantified performance across sample size and correlation conditions, and introduced the dynamic stress signature framework for longitudinal PCA.

The key findings are four. PCA recovers the true burnout component structure reliably at $n \geq 200$ (Tucker $\varphi \geq 0.95$ in 94% of replications) and fails frequently at $n \leq 40$ (36%). The AIC advantage of PCA over raw-variable regression is consistent across all conditions tested (ΔAIC = 14.7 to 17.1), driven primarily by

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parsimony rather than multicollinearity correction alone. MSE reduction is largest at small n, where multicollinearity most damages OLS stability. Applied researchers should not apply PCA when mean inter-variable correlation falls below $|r| \approx 0.30$, as components lose scientific interpretability even when computational recovery remains feasible.

The dynamic stress signature extends these cross-sectional findings into a longitudinal framework. Each student's characteristic sequence of dominant components across the academic calendar is individually unique, clinically actionable, and recoverable by projecting new data onto the baseline loading matrix without refitting. The signature identifies at-risk students before aggregate scores reach actionable thresholds and provides institutions with a population-level stress ecology indicator that tracks the impact of wellbeing interventions across academic years.

The simulation design, sensitivity tables, and longitudinal framework together constitute a complete methodological guide for applied burnout researchers deploying PCA in behavioral datasets. The Python simulation code is available from the author on request.

1 *The dynamic stress signature concept draws on an analogy from Bach Flower Remedy practice (Bach, 1936; Chancellor, 1971), in which each individual presents a shifting pattern of dominant emotional states — not a fixed diagnosis — and the practitioner tracks the current leading state to select the appropriate remedy. The parallel to longitudinal PCA is direct: no two individuals share the same state sequence over time, just as no two students share the same component trajectory across the academic calendar. The authors credit this clinical framework as the original motivation for the individual-signature hypothesis.*

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