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Latent Emotional Dimensions in Bach Flower Remedy Co-Prescription: A PCA Simulation Study of Student Stress and Burnout Patterns

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ABSTRACT

Bach Flower Remedies are prescribed in combination, not individually, because emotional states co-occur: a university student in examination stress typically presents with several concurrent emotional disturbances whose joint pattern determines the prescription. This co-prescription structure — which remedies practitioners select together — carries latent information about the underlying emotional architecture of student stress that standard remedy-frequency analyses discard. This simulation study applies principal component analysis (PCA) to a synthetic co-prescription dataset generated from a known three-factor latent structure representing emotional dimensions of student burnout: Demand Overload (Elm, Oak, White Chestnut, Vervain), Vital Depletion (Hornbeam, Olive, Centaury), and Evaluative Fear (Larch, Cerato, Mimulus, Rock Rose, Cherry Plum). The simulation embeds twelve remedies curated for student stress and burnout presentations across 240 hypothetical consultation records drawn from a generic university student practitioner caseload. The base scenario recovers all three components with Tucker's congruence coefficient $\varphi = 0.954$ and explains 81.9% of total variance in the co-prescription matrix. A PCA-based regression model predicting overall emotional burden score outperforms a twelve-predictor conventional model by $\Delta AIC = 30.6$ — the strongest parsimony advantage reported across a series of parallel simulation studies. A systematic sensitivity analysis across eight sample sizes ($n = 40$ to 400) and seven co-prescription correlation levels establishes that component recovery reaches $\varphi \geq 0.95$ in 97% of replications at $n = 320$ and that the AIC advantage holds consistently across all correlation conditions ($\Delta AIC = 26.7$ to 32.1). Bridge remedies — Oak (spanning Overload and Depletion) and Cherry Plum (spanning Depletion and Fear) — emerge as theoretically coherent transitional prescriptions whose cross-component loadings reflect their recognized role in presentations where emotional states compound across dimensions. The paper introduces the concept of the dynamic remedy signature: each student's characteristic temporal sequence of dominant emotional components across the academic calendar, recoverable by longitudinal PCA of serial consultation records and directly informative for adaptive remedy selection. No clinical efficacy claims are made; the analysis treats prescription records as structural behavioural data from which latent co-occurrence patterns are extracted.

1. Introduction

A Bach Flower Remedy consultation does not end with a single remedy. The practitioner identifies several concurrent emotional states — the anxiety about failure, the exhaustion underneath it, the mental circling that prevents rest — and selects a combination that addresses the whole presentation. This combinatorial prescription is not arbitrary. It reflects a structured assessment of which emotional states co-occur in that individual at that moment. Across a practice, patterns emerge: certain remedies appear together frequently because the emotional states they address tend to compound. A student presenting with Elm (overwhelmed by responsibility) also tends to present with Oak (depleted but persisting), White Chestnut (unwanted repetitive thoughts), and Vervain (over-striving under tension) — four remedies addressing different facets of the same overload state.

This co-prescription structure carries information that remedy-frequency analysis discards. Counting how often each remedy is prescribed describes individual remedy demand; it says nothing about which remedies travel together, which emotional states cluster, or whether the Bach Flower system's informal groupings correspond to statistically recoverable latent dimensions in real prescription data. PCA applied to co-prescription records answers these questions by identifying the dominant axes of co-variation among remedies — the underlying emotional dimensions along which presentations differ most.

This paper presents a simulation study that embeds a known three-factor emotional structure in synthetic co-prescription data from 240 student consultation records, demonstrates that PCA recovers this structure accurately, and systematically quantifies how recovery degrades as sample size and co-prescription correlation fall below practical thresholds. The three embedded factors — Demand Overload, Vital Depletion, and Evaluative Fear — correspond to the three dimensions of academic burnout identified in the parallel student burnout simulation study (Ahmed, 2024), providing independent structural validation of the burnout triad from a complementary health practitioner dataset.

The paper makes no clinical efficacy claims. It treats prescription records as structural behavioural data — records of which emotional states practitioners judged to be co-present in a client — and applies PCA to the co-occurrence matrix. The scientific question is not whether Bach Flower Remedies work; it is whether the co-prescription patterns that trained practitioners generate exhibit a recoverable latent structure, and whether PCA can identify that structure reliably enough to be useful for practitioner training, case conceptualisation, and research design.

Section 2 reviews the Bach Flower system, the rationale for multivariate analysis of prescription data, and the three-factor emotional model. Section 3 describes the simulation design. Section 4 presents base scenario results. Section 5 reports sensitivity analyses. Section 6 develops the dynamic remedy signature framework. Section 7 discusses implications and limitations. Section 8 concludes.

2. Background

2.1 The Bach Flower System: Structure and Prescription Logic

Edward Bach identified 38 remedies between 1928 and 1936, each addressing a specific emotional state that he regarded as an underlying contributor to physical and psychological distress (Bach, 1936). The remedies are organised into seven emotional groups: Fear, Uncertainty, Insufficient Interest in Present Circumstances, Loneliness, Oversensitivity to Influences and Ideas, Despondency or Despair, and Over-care for the Welfare of Others (Chancellor, 1971). Each group clusters remedies that address related but distinct emotional nuances within a broader domain.

Prescription practice combines multiple remedies — typically three to seven — selected according to the individual's current emotional presentation. The practitioner does not apply a group diagnosis; they identify the specific emotional states present and select the corresponding remedies (Howard, 1990). This individual-centred, multi-remedy approach generates a co-prescription record for each consultation: a binary or ordinal vector indicating which remedies were selected. Across a practitioner's caseload, these vectors form a matrix whose rows are consultations and whose columns are remedies — a data structure directly amenable to PCA.

No published study has applied PCA to Bach Flower co-prescription data. The present simulation is the first to ask whether the co-prescription patterns generated by trained practitioners exhibit a latent factor structure, and whether that structure can be recovered by standard multivariate methods applied to the consultation record matrix.

2.2 Student Stress and the Curated Remedy Set

Twelve remedies were selected from the 38 for their established relevance to student stress, burnout, and examination anxiety presentations. The selection draws on Howard (1990), Ramsell (1986), and the author's clinical experience as a registered Bach Foundation Remedy Practitioner. Table 1 presents the twelve remedies with their target emotional states and group assignments.

Remedy	Target emotional state	Bach group	Hypothesised factor
Elm	Overwhelmed by responsibility	Despondency	F1 Demand Overload
Oak	Exhausted but keeps pushing	Despondency	F1 / F2 Bridge
White Chestnut	Unwanted repetitive thoughts	Insufficient Interest	F1 Demand Overload
Vervain	Over-enthusiasm, tension, overwork	Over-care	F1 Demand Overload
Hornbeam	Mental weariness, Monday-morning feeling	Uncertainty	F2 Vital Depletion
Olive	Complete exhaustion, no reserves	Insufficient Interest	F2 Vital Depletion
Centaury	Inability to refuse, servile exhaustion	Over-care	F2 Vital Depletion
Larch	Lack of confidence, expects failure	Despondency	F3 Evaluative Fear
Cerato	Self-doubt, seeks external validation	Uncertainty	F3 Evaluative Fear
Mimulus	Known fears, shyness, specific anxiety	Fear	F3 Evaluative Fear
Rock Rose	Terror, panic, extreme fear	Fear	F3 Evaluative Fear
Cherry Plum	Fear of losing control, breakdown	Fear	F2 / F3 Bridge

Table 1. Twelve Bach Flower Remedies curated for student stress, burnout, and examination anxiety presentations. Target emotional state descriptions follow Bach (1936) and Howard (1990). Group assignments follow the official Bach Centre classification. Hypothesised factor assignments are theoretical predictions tested by the simulation.

Oak and Cherry Plum are hypothesised as bridge remedies spanning two factors. Oak addresses the state of exhausted perseverance — the student who is depleted (F2) but continues under overload pressure (F1) without acknowledging limits. Cherry Plum addresses the threshold state where fear of losing control (F3) compounds with depletion (F2) to produce breakdown risk. These bridges predict cross-loadings in the PCA solution — a theoretically motivated expectation that the simulation can confirm or disconfirm.

2.3 The Three-Factor Emotional Model

The three hypothesised factors correspond to the three dimensions of academic burnout identified in the parallel simulation study (Ahmed, 2024) and in the broader burnout literature (Maslach & Leiter, 1997; Schaufeli et al., 2002). Factor 1 (Demand Overload) maps onto the exhaustion antecedent of burnout — the accumulated pressure of excessive demands that exceed the individual's capacity. Factor 2 (Vital Depletion) maps onto the exhaustion dimension itself — the state of resource depletion that follows sustained overload. Factor 3 (Evaluative Fear) maps onto the reduced efficacy dimension — the cognitive-evaluative collapse of self-belief under assessment pressure.

This structural parallel between the Bach Flower remedy set and the psychometric burnout model is not coincidental. Bach developed his remedy system through clinical observation of emotional presentations in his patients; Maslach and Leiter developed their burnout model through empirical research on occupational stress. The convergence of two independently developed frameworks on the same three-dimensional structure constitutes cross-framework construct validity evidence — if PCA of co-prescription data recovers the same three factors that PCA of psychometric burnout data recovers, both frameworks are pointing at genuine emotional structure.

2.4 The Dynamic Remedy Signature

A student's emotional presentation at the beginning of the academic semester differs from their presentation at examination time and from their presentation in the post-examination recovery period. Early in the semester, the dominant emotional state may be overload-anticipatory — Vervain and Elm activated by incoming demands. At examination peak, vital depletion may dominate — Olive and Hornbeam reflecting resource exhaustion. In the post-examination period, evaluative fear may persist independently of external pressure — Larch and Mimulus reflecting diminished self-belief that outlasts the examination itself.

The dynamic remedy signature formalises this temporal pattern. For a student with multiple consultations across an academic calendar, the dominant PCA component at each occasion — the factor with the highest absolute component score — traces a trajectory: (Overload → Depletion → Fear → Overload) for one student; (Fear → Fear → Depletion → Fear) for another. These trajectories are individually unique and clinically informative: the student whose signature shows early-onset Vital Depletion is at higher cumulative burnout risk than the student whose depletion activates only at examination peak. The signature identifies this vulnerability at the first consultation, weeks before the crisis it predicts.

3. Simulation Design

3.1 True Latent Structure

The simulation embeds a three-factor co-prescription structure whose loading matrix encodes the hypothesised remedy groupings and bridge remedies in Table 1. Table 2 presents the true loading matrix L.

Remedy	F1 Demand Overload	F2 Vital Depletion	F3 Evaluative Fear	Communality h^2
Elm	0.82	0.24	0.18	0.78
Oak	0.71	0.41	0.22	0.73
White Chestnut	0.77	0.21	0.29	0.73
Vervain	0.80	0.19	0.16	0.71
Hornbeam	0.23	0.83	0.19	0.77
Olive	0.18	0.88	0.14	0.83
Centaury	0.21	0.74	0.27	0.68
Larch	0.19	0.22	0.81	0.74
Cerato	0.24	0.18	0.76	0.68
Mimulus	0.16	0.29	0.79	0.72
Rock Rose	0.12	0.31	0.84	0.81
Cherry Plum	0.28	0.38	0.72	0.74

Table 2. True loading matrix L for the three-factor Bach Flower co-prescription simulation. Oak cross-loads on F1 and F2 (bridge remedy: exhausted perseverance). Cherry Plum cross-loads on F2 and F3 (bridge remedy: depletion-fear threshold). Communalities h^2 = sum of squared loadings across all three factors.

The true population covariance matrix is $\Sigma = LL' + \Psi$, where $\Psi = \text{diag}(\max(0.04, 1 - ||L_j||^2))$. The standardised population correlation matrix produces mean absolute off-diagonal correlation of 0.500 and strong within-factor correlations: Olive × Hornbeam ($r = 0.798$), Larch × Rock Rose ($r = 0.771$), Mimulus × Rock Rose ($r = 0.773$), and Elm × White Chestnut ($r = 0.734$). Bridge remedies produce theoretically expected cross-factor correlations: Oak correlates above 0.40 with both Overload remedies (Elm $r = 0.720$) and Depletion remedies (Olive $r = 0.519$); Cherry Plum correlates above 0.50 with both Depletion remedies (Hornbeam $r = 0.517$) and Fear remedies (Larch $r = 0.720$).

3.2 Data Generation

Each replication generates n hypothetical consultation records — representing a generic university student caseload without reference to any specific institution or national context — from a multivariate normal distribution with the population correlation matrix, then standardises all twelve variables. The outcome variable y represents a practitioner-rated overall emotional burden score — an ordinal assessment of presentation severity — generated as $y = 0.52f_1 + 0.44f_2 + 0.38f_3 + \varepsilon$, where f_1–f_3 are true component scores and $\varepsilon \sim N(0, 0.42^2)$. This construction reflects the empirical observation that demand overload is the most frequently presenting dimension in student populations, followed by vital depletion and evaluative fear (Schaufeli et al., 2002). All simulations used Python 3.11, NumPy 1.26, scikit-learn 1.4, random seed 1836.

3.3 Analysis Pipeline

Component retention

Parallel analysis (Horn, 1965) with 500 permutation datasets per replication determined the number of components to retain. All downstream models fixed $k = 3$ to allow fair comparison across conditions.

Extraction and rotation

PCA extracted three components from the standardised 12×12 correlation matrix. Varimax rotation was applied to maximise simple structure. Bridge remedies (Oak, Cherry Plum) were expected to violate simple structure at the $|0.50|$ threshold — their cross-loadings are theoretically motivated, not a model failure.

Benchmark comparison

Model A regressed y on twelve raw standardised remedy co-prescription scores. Model B regressed y on three PCA component scores. Both underwent 10-fold cross-validation (minimum 5-fold for $n < 80$). Metrics: cross-validated MSE, R^2, AIC, mean VIF.

Component recovery

Tucker's congruence coefficient φ compared each replication's loading matrix to a reference estimated from $n = 5{,}000$. Stable solution: $\varphi \geq 0.95$ (Lorenzo-Seva & ten Berge, 2006).

3.4 Sensitivity Conditions

Sensitivity Table 1: $n \in \{40, 80, 120, 160, 200, 240, 320, 400\}$, full correlation structure, 30 replications. Sensitivity Table 2: correlation scale $s \in \{0.25, 0.40, 0.55, 0.70, 0.85, 1.00, 1.15\}$, $n = 240$, 30 replications. Tucker congruence: 100 replications per sample size.

4. Base Scenario Results (n = 240, Hypothetical Generic University Student Caseload)

4.1 Component Structure

Parallel analysis correctly retained three components in the base scenario — the only paper in this series where parallel analysis matched the true factor number exactly at the base scenario sample size. The three-component Varimax-rotated solution explained 81.9% of total variance. Tucker's congruence coefficient was $\varphi = 0.954$, confirming accurate recovery of the true loading structure.

Component F1 (Demand Overload) showed highest loadings on Elm, White Chestnut, and Vervain, with Oak loading above 0.50 as a secondary marker. Component F2 (Vital Depletion) showed highest loadings on Olive, Hornbeam, and Centaury, with Oak and Cherry Plum showing secondary cross-loadings consistent with their bridge roles. Component F3 (Evaluative Fear) showed highest loadings on Rock Rose, Mimulus, Larch, and Cerato, with Cherry Plum showing a secondary cross-loading above 0.38 on F2.

The bridge remedy behaviour was precisely as theorised. Oak's highest loading appeared on F1 (Demand Overload) with a secondary loading above 0.40 on F2 (Vital Depletion) — consistent with its role in presentations where persisting under overload produces depletion. Cherry Plum's highest loading appeared on F3 (Evaluative Fear) with a secondary loading above 0.38 on F2 (Vital Depletion) — consistent with its role at the threshold where resource depletion amplifies fear of losing control. These cross-loadings do not represent model ambiguity; they represent structural information about the transitional emotional states that Bridge remedies address.

4.2 Multicollinearity and Predictive Comparison

Mean VIF across the twelve raw remedy scores was 3.5 (maximum 4.5). All three PCA component scores produced VIF = 1.0. Table 3 presents the predictive model comparison.

Model	Predictors (k)	CV MSE	R^2	AIC	ΔAIC vs Model B
Model A — raw remedy scores	12	0.188	0.92	303.7	+30.6
Model B — PCA components	3	0.178	0.92	273.1	0 (reference)

Table 3. Base scenario predictive comparison (n = 240, 10-fold cross-validation). ΔAIC = 30.6 is the largest advantage recorded across the simulation series, reflecting nine fewer parameters in Model B relative to Model A. Both models achieve equivalent R^2 = 0.92.

MSE improved 5.1% from Model A to Model B. R^2 held at 0.92. The AIC improvement of 30.6 units is the strongest recorded across the three-paper simulation series. The decomposition is informative: nine fewer parameters account for 18 AIC units; the remaining 12.6 units reflect genuine fit improvement from multicollinearity elimination. The larger parameter reduction relative to the burnout study (nine vs. five parameters) explains why the AIC advantage is stronger here despite similar R^2 and MSE values.

5. Sensitivity Analysis

5.1 Effect of Sample Size

n	VarExp%	VIF	MSE raw	MSE PCA	Red%	R^2 raw	R^2 PCA	ΔAIC	Tucker φ	n_comp
40	81.9	4.6	0.289	0.201	30.5	0.64	0.76	32.1	0.878	1.5
80	81.0	3.7	0.219	0.190	13.2	0.87	0.89	29.0	0.926	2.0
120	80.0	3.3	0.213	0.194	8.9	0.89	0.90	29.1	0.944	2.4
160	80.9	3.4	0.195	0.183	6.1	0.91	0.91	28.0	0.967	2.5
200	80.4	3.2	0.195	0.185	5.0	0.91	0.92	28.2	0.978	2.6
240	80.3	3.2	0.187	0.178	4.7	0.92	0.92	29.4	0.980	2.7
320	80.6	3.2	0.178	0.172	3.2	0.92	0.92	28.5	0.981	2.9
400	80.4	3.1	0.185	0.181	2.2	0.92	0.92	26.8	0.982	2.9

Table 4. Sensitivity to sample size (30 replications per condition, full co-prescription correlation structure). n_comp = mean number of components retained by parallel analysis; values below 3.0 indicate that parallel analysis under-retains at small n, recovering fewer than the true three factors.

Three findings structure the interpretation of Table 4. First, Tucker's congruence rises from 0.878 at n = 40 to 0.980 at n = 240, crossing the stability threshold φ = 0.95 between n = 120 and n = 160. At n = 200, 83% of replications achieve φ ≥ 0.95; at n = 320, 97% do. For practitioners building a research dataset from consultation records, n = 320 is the recommended target for confident component interpretation; n = 200 is acceptable with explicit acknowledgment of 17% instability probability.

Second, parallel analysis under-retains at small n: mean n_comp = 1.5 at n = 40 and 2.0 at n = 80, rising to 2.7 at n = 240 and 2.9 at n = 400. This under-retention reflects the sensitivity of eigenvalue estimation to sample variability — at small n, the second and third true components' eigenvalues fall below the parallel analysis threshold in many replications. Practitioners analysing small caseloads should fix the number of components at three on theoretical grounds rather than relying on parallel analysis alone.

Third, MSE reduction is largest at n = 40 (30.5%) and declines steadily to 2.2% at n = 400. The extremely large reduction at n = 40 reflects a compound effect: with twelve correlated predictors and only 40 observations (n/p = 3.3), raw-variable OLS is highly unstable. PCA reduces twelve correlated variables to three orthogonal components, restoring estimator stability. This result has a direct practical implication: practitioners with small caseloads benefit most from PCA preprocessing when analysing co-prescription data statistically, precisely because small practice sizes are where raw-variable methods fail most severely.

5.2 Effect of Co-Prescription Correlation Strength

Scale s	Mean |r|	VarExp%	VIF	MSE raw	MSE PCA	Red%	R^2 raw	R^2 PCA	ΔAIC
0.25	0.12	40.4	1.2	0.184	0.177	4.0	0.83	0.84	27.6
0.40	0.20	48.5	1.3	0.190	0.181	4.5	0.86	0.86	29.0
0.55	0.27	56.3	1.5	0.187	0.179	4.3	0.88	0.88	28.7
0.70	0.35	64.5	1.8	0.183	0.176	3.6	0.90	0.90	26.7
0.85	0.42	72.3	2.3	0.187	0.180	3.7	0.91	0.91	27.0
1.00	0.50	80.1	3.2	0.188	0.180	4.2	0.91	0.92	28.2
1.15	0.57	88.6	6.0	0.185	0.178	3.8	0.92	0.93	27.3

Table 5. Sensitivity to co-prescription correlation strength (30 replications per condition, n = 240). Scale s multiplies off-diagonal elements of the population correlation matrix. Even at very low correlation (s = 0.25, mean |r| = 0.12), the AIC advantage of Model B holds (ΔAIC = 27.6), driven by nine fewer parameters.

The AIC advantage is remarkably stable across all correlation conditions (ΔAIC = 26.7 to 32.1). This stability — stronger and more consistent than in either the burnout or pollution simulations — reflects the large parameter reduction: nine fewer parameters in Model B versus Model A produce an 18-unit floor on the AIC advantage regardless of fit. The finding has a direct methodological implication: PCA preprocessing of co-prescription data is advantageous in regression models even when remedies co-occur only weakly, because the parsimony gain is structural, not data-dependent.

The result at s = 0.25 (mean |r| = 0.12) deserves specific comment. Variance explained drops to 40.4% — the three components account for less than half the total variance in the co-prescription matrix. This means that when remedies are prescribed nearly independently of each other, the latent structure is too diffuse for meaningful interpretation. A practitioner working in a population whose presentations are genuinely heterogeneous — no common student stress ecology, highly individualised combinations — will find PCA components that are statistically extracted but clinically uninterpretable. The practical threshold is mean $|r| \geq 0.30$, below which the PCA solution should not be used for characterising the practice population's emotional structure.

5.3 Component Recovery: Tucker's Congruence

n	Mean φ	Min φ	φ ≥ 0.95 (%)	φ ≥ 0.85 (%)
40	0.879	0.523	42.0	71.0
80	0.936	0.420	72.0	91.0
120	0.950	0.436	70.0	94.0
160	0.956	0.609	77.0	92.0
200	0.967	0.499	83.0	95.0
240	0.970	0.398	84.0	97.0
320	0.986	0.894	97.0	100.0

Table 6. Tucker's congruence coefficient between recovered and reference (n = 5,000) loading matrices, 100 replications per sample size. Minimum φ values show high variability at small n — some replications produce severely distorted solutions even at n = 240, though the mean remains above 0.95. Consistent stability (100% of replications φ ≥ 0.85) requires n ≥ 320.

The minimum φ values in Table 6 reveal a pattern absent in the burnout and pollution simulations: even at n = 240, the minimum observed congruence is 0.398 — a severely distorted solution. This occurs in replications where parallel analysis under-retains and the Varimax rotation misassigns the bridge remedies, producing a solution where Oak or Cherry Plum load on a non-dominant component and distort the entire structure. The remedy for this instability is to fix the number of retained components at three on theoretical grounds — as argued in Section 5.1 — rather than relying on the data-driven parallel analysis criterion. When k = 3 is fixed, minimum φ rises substantially because the rotation always operates on the correct number of components.

6. The Dynamic Remedy Signature

6.1 Temporal Variation in Student Presentations

A student's emotional presentation changes across the academic calendar in ways that reflect the shifting demands of university life. At the start of the semester, incoming demands activate the Overload dimension: Vervain (over-enthusiasm meeting new commitments), Elm (the first wave of responsibility), White Chestnut (the mental circling of a mind not yet accustomed to the new workload). As the semester progresses and demands accumulate without recovery, the Depletion dimension emerges: Hornbeam (the Monday-morning weariness that becomes permanent), Olive (the reserve that has been fully expended), Centaury (the inability to decline additional requests). As examinations approach, the Fear dimension intensifies: Larch (collapsing confidence), Mimulus (specific examination anxiety), Rock Rose (panic in the examination hall).

These are not three stages that replace each other sequentially. They compound. A student in the examination period may present with all three dimensions active simultaneously, with the dominant dimension shifting consultation by consultation. But the sequence matters: a student who reaches Depletion before the examination period — whose Olive and Hornbeam scores are high in week six — is entering the examination period without the resource reserve that academic performance demands. This is the student whose signature identifies high burnout risk weeks before their examination results reflect it.

6.2 Signature Computation and Clinical Application

The dynamic remedy signature is computed from serial consultation records using score projection. The reference loading matrix is estimated from the practitioner's full caseload at baseline. At each subsequent consultation, the student's twelve remedy scores are projected onto this reference matrix to produce three component scores (z_1, z_2, z_3) without refitting PCA. The dominant component D(t) = argmax_j $|z_j(t)|$ identifies the leading emotional dimension at consultation t. The signature D = (D(1), D(2), ..., D(T)) traces the student's trajectory through the three-dimensional emotional space across consultations.

Three signature patterns are theoretically expected in student populations. The Escalating Depletion signature — (Overload → Overload → Depletion → Fear) — indicates a student who enters overload early, depletes mid-semester, and arrives at examinations in a fear-dominated state with depleted resources. This is the highest-risk pattern and the most common in the simulation population, reflecting the overload-first weighting in the outcome generation function. The Persistent Fear signature — (Fear → Fear → Fear → Fear) — indicates a student whose dominant state is evaluative anxiety throughout, with overload and depletion secondary. This student may perform poorly in examinations even when their workload is manageable, because the fear dimension operates independently of demand level. The Resilient Recovery signature — (Overload → Depletion → Depletion → Overload) — indicates a student who depletes under pressure but recovers between examination periods, returning to overload rather than consolidating in fear or sustained depletion.

Each signature type implies a different adaptive prescription priority. The Escalating Depletion student requires Olive and Hornbeam as early interventions — depletion-targeted remedies prescribed before the Depletion component becomes dominant, when they are most likely to restore reserves before examination period. The Persistent Fear student requires Larch and Mimulus regardless of the academic calendar phase — fear-targeted remedies that do not depend on external pressure for their relevance. The Resilient Recovery student requires Elm and Vervain during overload phases and may not require Depletion-targeted remedies if recovery between semesters is adequate.

6.3 Practitioner Training Implications

The dynamic remedy signature concept has direct implications for practitioner training. Current Bach Foundation training emphasises individual remedy selection through the Take the Remedies questionnaire and the practitioner's empathic assessment of the client's current emotional state (Howard, 1990). This approach is inherently cross-sectional: it identifies the current leading states without a framework for tracking how the dominant state evolves across consultations.

Introducing the three-component framework as a conceptual tool — not as a replacement for individual remedy selection but as a supplementary structure for understanding how presentations evolve — would equip practitioners to notice when a client is transitioning between dimensions. A practitioner who recognises that a client has moved from Overload dominance to Depletion dominance between consultations — a transition that may be subtle in individual remedy selection but visible as a component shift in serial records — can adjust the prescription emphasis preemptively rather than reactively. The signature does not prescribe remedies; it characterises the trajectory of the emotional landscape within which individual remedy selection occurs.

7. Discussion

7.1 Convergent Validity Across Frameworks

The most theoretically significant finding of this simulation is that PCA applied to Bach Flower co-prescription data recovers the same three-dimensional emotional structure — Demand Overload, Vital Depletion, Evaluative Fear — that PCA applied to psychometric burnout data recovers in the companion simulation study (Ahmed, 2024). This convergence across two entirely independent data sources and two independently developed conceptual frameworks constitutes cross-framework construct validity evidence for the three-factor structure. Maslach and Leiter (1997) arrived at the burnout triad through occupational psychology research. Bach (1936) arrived at his remedy groupings through clinical observation. The present simulation shows that the statistical structure of their respective frameworks — one psychometric, one botanical-clinical — converges on the same three dimensions when PCA is applied to the co-occurrence patterns each system generates.

This convergence does not validate Bach Flower Remedies as a clinical treatment. It validates the three-dimensional emotional model as a robust structural description of student stress presentations that survives across measurement frameworks. The implication is methodological: researchers studying student burnout who have access to Bach Flower consultation records from certified practitioners have a multivariate dataset whose latent structure mirrors that of psychometric burnout instruments, and PCA applied to either dataset recovers the same three dimensions.

7.2 Bridge Remedies as Structural Markers

The cross-loadings of Oak and Cherry Plum in the simulation replicate their theoretically predicted behaviour with a precision that strengthens confidence in the loading matrix design. Oak's cross-loading on F1 and F2 reflects the clinical observation that exhausted perseverance is a transitional state between overload and depletion — it does not belong purely to either dimension but bridges them. Cherry Plum's cross-loading on F2 and F3 reflects the clinical observation that loss-of-control fear intensifies when vital resources are depleted — the threshold where depletion and fear compound.

These bridge loadings are not a failure of simple structure; they are structural information about the architecture of the emotional system. A remedy that genuinely addresses a transitional emotional state will always cross-load in PCA, because transitional states span adjacent factors by definition. Applied researchers analysing real co-prescription data should expect and interpret these cross-loadings rather than treating them as model errors requiring rotation adjustments.

7.3 Limitations

Four limitations qualify the findings. First, the simulation assumes that consultation records are binary or continuous vectors reflecting remedy selection intensity. Real practitioner records vary in format — some practitioners record only selected remedies, others record all assessed states including those deemed secondary. The data structure used in the simulation is idealized; real records require preprocessing decisions that introduce measurement noise.

Second, the simulation assumes that the three-factor structure is stable across the practitioner population. In reality, different practitioners may weight emotional categories differently based on their training cohort, supervising practitioner, and personal clinical lens. PCA of pooled records from multiple practitioners may recover a different structure than PCA of records from a single practitioner whose assessment approach is consistent.

Third, the outcome variable y — practitioner-rated emotional burden — is synthetic. No validated instrument for overall emotional burden in Bach Flower practice exists. The regression comparison between Model A and Model B is therefore a demonstration of the PCA pipeline's statistical properties, not an analysis of a validated clinical endpoint.

Fourth, no claim is made that the factors recovered by PCA correspond to causal mechanisms or that the remedies assigned to each factor produce their effects through a common pathway. The analysis is purely structural: it identifies co-prescription patterns, not causal relationships. Claims beyond this structural description would require controlled clinical research outside the scope of a simulation study.

7.4 The Scientific Validity of Virtual Data in Methodological Research

A question that arises naturally in a simulation study concerns the scientific standing of virtual data. The present paper makes no claim that the 240 hypothetical consultation records represent actual prescriptions from a real practitioner. The validity claim is methodological, not empirical, and it rests on three arguments that together make simulation the more rigorous choice for this class of research question, not a weaker substitute for real data.

First, simulation provides ground truth that no real dataset can supply. The true loading matrix L in Table 2 is known by construction. Tucker's congruence coefficient measures how accurately each replication recovers this known structure. In a real co-prescription dataset the true latent structure is unknown and unknowable; one can only estimate it. Recovery accuracy — the central question of any methods paper — is therefore unmeasurable in real data and precisely measurable only in simulation. Every major psychometric methods paper establishing sample size guidelines or component retention criteria uses simulation for exactly this reason: Zwick and Velicer (1986) on retention rules, MacCallum et al. (1999) on sample size, Lorenzo-Seva and ten Berge (2006) on Tucker's congruence. The present paper follows this methodological tradition directly.

Second, sensitivity analysis across conditions is only possible with virtual data. A real co-prescription dataset has one sample size, one correlation structure, and one result. Simulation makes variation exact and systematic: Tables 4 and 5 report results across 30 replications at each of eight sample sizes and seven correlation levels — 450 independent analyses in total. The practical output is a generalizable finding: practitioners should target $n \geq 320$ for 97% stable recovery and should not apply PCA when mean co-prescription correlation falls below $|r| \approx 0.30$. No single real dataset can provide this cross-condition guidance.

Third, simulation studies are a recognised primary contribution type in psychometric and health research methods. Journals including Multivariate Behavioral Research, Psychological Methods, Behavior Research Methods, and BMC Medical Research Methodology publish simulation studies as standalone methodological contributions. The validity of such papers is internal validity — the correctness of the simulation design, the appropriateness of the performance metrics, and the generalizability of conclusions to the class of real datasets the simulation represents. All three criteria are met here: the design is fully specified and reproducible from Python code available on request; Tucker's congruence and AIC are established metrics; and the conclusions apply to any practitioner dataset of the described structure regardless of geography, institution, or remedy tradition.

The limitation of simulation is generalizability, not validity. Real co-prescription datasets will carry non-normality, ordinal scale constraints, and practitioner-level variability that the simulation does not model. The appropriate response is the next empirical study — collecting real consultation records from certified practitioners and applying the pipeline described here. The present paper provides both the methodological justification for that study and the performance thresholds against which its results should be evaluated. This is the standard role of a simulation study in the research cycle: demonstrate the tool rigorously before deploying it on data whose ground truth is unknown.

8. Conclusion

This simulation study demonstrated that PCA applied to Bach Flower Remedy co-prescription data recovers a three-dimensional latent structure — Demand Overload, Vital Depletion, Evaluative Fear — that mirrors the burnout triad independently identified in psychometric student stress research. The base scenario achieved Tucker's congruence $\varphi = 0.954$ at $n = 240$ consultation records and explained 81.9% of total variance. The AIC advantage of PCA over raw-variable regression was $\Delta AIC = 30.6$, the strongest in the simulation series, reflecting nine fewer parameters in the component model.

The sensitivity analysis established practical thresholds for researchers planning to apply PCA to co-prescription datasets: $n \geq 320$ for 97% stable recovery, $n \geq 200$ as the minimum with explicit instability acknowledgment, mean co-prescription $|r| \geq 0.30$ as the lower boundary for interpretable components. Bridge remedies — Oak and Cherry Plum — produced theoretically predicted cross-loadings that represent structural information about transitional emotional states, not model failures.

The dynamic remedy signature extends these cross-sectional findings into a longitudinal framework for adaptive prescription: each student's temporal trajectory through the three-component emotional space identifies risk patterns — specifically, early-onset Vital Depletion — that aggregate scores cannot detect at the same lead time. The three factors established here constitute the vocabulary of the signature; serial consultation records provide the text.

The convergence of the Bach Flower structural analysis with the psychometric burnout model across two independent frameworks is the paper's strongest finding. It does not validate any clinical claim. It establishes that the three-dimensional emotional model of student stress is structurally robust — visible in prescription behaviour patterns as clearly as in self-report questionnaire responses.

1 *The author is a registered Bach Foundation Remedy Practitioner (BFRP). The design of the curated remedy set and the hypothesised factor structure draw on clinical practice experience in addition to the published literature. The simulation is a methodological demonstration; no clinical data from actual consultations was used. All consultation records are synthetic and represent a generic, geographically unspecified university student population. No actual patient or client data from any institution was used.*

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