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Unsupervised Machine Learning–Based Identification of Psychosomatic Susceptibility Profiles Using Big Five Personality Traits, Alexithymia, Coping Flexibility, Sleep Disturbance, and Somatic Symptom Severity

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ABSTRACT

This study aimed to identify psychosomatic susceptibility profiles among adults in Ireland using unsupervised machine learning based on Big Five personality traits, alexithymia, coping flexibility, sleep disturbance, and somatic symptom severity. A cross-sectional, person-centered study included 713 adults residing in the Republic of Ireland. Participants completed the Big Five Inventory–2 Short Form, Toronto Alexithymia Scale, Coping Flexibility Scale, Pittsburgh Sleep Quality Index, and Patient Health Questionnaire–15. Standardized scores were analyzed using k-means clustering, partitioning around medoids, Gaussian mixture modeling, and hierarchical clustering. Solutions containing two to six profiles were compared using silhouette width, the Calinski–Harabasz index, the Davies–Bouldin index, the gap statistic, bootstrap Jaccard coefficients, and holdout adjusted Rand indices. Profile differences were examined using omnibus tests, adjusted pairwise comparisons, and effect sizes. A four-profile solution provided the strongest and most stable fit, comprising resilient–low susceptibility, emotionally constrained, sleep-disturbed negative affect, and multidimensional high susceptibility profiles. Significant between-profile differences were found for all clustering indicators (all $p < .001$). The largest effects emerged for somatic symptom severity, $F(3, 709) = 344.79$, partial $\eta^2 = .593$; negative emotionality, $F(3, 709) = 318.57$, partial $\eta^2 = .574$; sleep disturbance, $F(3, 709) = 301.66$, partial $\eta^2 = .561$; alexithymia, $F(3, 709) = 283.12$, partial $\eta^2 = .545$; and coping flexibility, $F(3, 709) = 271.40$, partial $\eta^2 = .535$. Profile membership was significantly associated with chronic physical illness, diagnosed mental health conditions, and psychotropic medication use. Psychosomatic susceptibility is best understood as a heterogeneous configuration of personality, emotional processing, coping adaptability, sleep impairment, and somatic burden, supporting profile-based assessment and targeted interventions.

Keywords: *psychosomatic susceptibility, unsupervised machine learning, Big Five personality traits, alexithymia, coping flexibility, sleep disturbance, somatic symptoms*

1. Introduction

Psychosomatic susceptibility refers to the tendency for psychological characteristics, emotional processing difficulties, stress-regulation patterns, and behavioral vulnerabilities to become expressed through bodily discomfort, functional somatic complaints, sleep disruption, pain, fatigue, autonomic arousal, or heightened attention to physical sensations. Contemporary psychosomatic models reject a strict separation between mental and physical processes and instead conceptualize health as the product of interacting biological, psychological, social, behavioral, and cultural mechanisms. This integrative position is consistent with evidence showing that psychological functioning can influence symptom perception, illness behavior, physiological regulation, treatment engagement, and adaptation to chronic health problems. Psychosomatic vulnerability is therefore unlikely to arise from a single psychological variable. It more plausibly reflects configurations of relatively stable personality traits, emotional awareness, coping resources, sleep-related impairment, and existing somatic symptom burden. Research conducted during periods of widespread stress has demonstrated that psychosomatic health is shaped by both individual predispositions and the capacity of the autonomic nervous system to adapt to sustained environmental demands (Pilafas & Lyrakos, 2021). Similarly, broad reviews of burnout indicate that physical and psychological exhaustion emerge through interconnected biological, psychological, social, spiritual, occupational, and cultural factors rather than through isolated causes (Listopad et al., 2021). A multidimensional approach is consequently necessary to distinguish adults who show adaptive functioning despite exposure to stress from those whose psychological characteristics may increase vulnerability to persistent bodily symptoms.

Personality provides a foundational framework for understanding individual differences in psychosomatic susceptibility because it influences emotional reactivity, health behavior, interpersonal functioning, coping selection, symptom appraisal, and the maintenance of daily routines. The Big Five model organizes personality into openness to experience, conscientiousness, extraversion, agreeableness, and negative emotionality, often termed neuroticism. These broad traits are relatively stable but remain relevant to modifiable behavioral and emotional processes. Recent research has linked Big Five traits to lifestyle patterns among university students, suggesting that personality may influence health indirectly through sleep habits, activity, substance use, diet, and other routine behaviors (Fukuti et al., 2026). Personality also contributes to emotional adjustment, resilience, and health-risk processes by shaping how individuals interpret threatening events and regulate their responses to adversity (Williams & Carlson, 2025). Positive personality characteristics may strengthen resilience across generations and support healthier adaptation to social and environmental challenges (Ranjbari, 2021). Conversely, dispositional vulnerability can amplify stress exposure and reduce the effectiveness of psychological adaptation. Evidence from occupational contexts indicates that personality interacts with job demands and occupational stress in predicting mental health among police officers (Esther & Obosi, 2023), while multilevel findings demonstrate that personality may alter the relationship between work-organization conditions and psychological distress (Parent-Lamarche et al., 2021). The relevance of personality is therefore not confined to internal emotional experience; it extends to the ways people encounter, interpret, and respond to external demands.

Among the Big Five dimensions, negative emotionality is particularly relevant to psychosomatic susceptibility because it involves a persistent tendency toward anxiety, irritability, worry, emotional instability, and heightened sensitivity to threat. Individuals with elevated negative emotionality may attend more closely to bodily changes, interpret ambiguous sensations more negatively, and experience greater physiological arousal during stress. Research on stress and personality during pandemic restrictions showed that personality characteristics influenced the intensity and quality of stress responses under prolonged uncertainty (Chauhan & Kumar, 2022). Studies of healthy adolescents have similarly identified preliminary relationships between temperament, personality, and multifactorial stress reactivity, indicating that dispositional differences can be reflected across psychological and physiological response systems (Ecker et al., 2025). In contrast, conscientiousness may protect health through self-regulation, adherence to routines, planning, and more consistent engagement in preventive behavior, while extraversion and agreeableness may facilitate access to social support and constructive interpersonal coping. Openness may promote cognitive flexibility and willingness to reconsider ineffective responses, although its relationship with physical symptoms is likely to depend on contextual and emotional factors. Research among Italian undergraduates has confirmed that personality traits are meaningfully associated with

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psychological well-being (Orrù et al., 2025), and work examining time perspective, morningness, and personality during lockdown further suggests that personality operates in combination with behavioral rhythms and temporal orientation rather than independently (Castellà & Muro, 2022). The psychosomatic implications of personality may thus be best understood through patterns of traits and their interaction with emotional and behavioral processes.

Personality traits have also been associated with specific mental and physical health conditions that commonly include somatic components. Big Five characteristics have been examined in relation to depression and suicidal behavior, with negative emotionality generally functioning as a vulnerability factor and more adaptive trait configurations contributing to psychological protection (Chen & Huang, 2024). A narrative review of childhood abuse, personality, and depression further suggests that adverse experiences may influence later mental health partly through their effects on personality development and enduring emotional vulnerability (Luo & Zhong, 2025). Personality and coping styles also possess diagnostic and predictive potential in major depressive disorder, indicating that trait-based and regulatory variables can jointly differentiate levels of clinical risk (Ho et al., 2022). Beyond mood disorders, personality-related vulnerability has been studied in behavioral conditions. A systematic review of gaming disorder emphasized the combined contribution of biological, psychological, and social factors, including personality characteristics and maladaptive coping processes (Chang et al., 2023). Psychopathological symptoms and personality traits likewise predict problematic smartphone use across age groups, illustrating how dispositional vulnerability may become expressed through behavior patterns that further interfere with sleep, functioning, and health (Wickord & Quaiser-Pohl, 2022). These findings support the view that personality should not be treated merely as a background characteristic; it may form part of identifiable vulnerability profiles that cut across diagnostic categories.

The relationship between personality and bodily symptoms is especially apparent in pain-related and medically unexplained conditions. A systematic review and meta-analysis of chronic headache found recurring associations between personality characteristics and persistent headache disorders, although the strength and form of these relationships differed across samples and measurement approaches (Bottiroli et al., 2023). Personality has also been proposed as a potential biomarker in fibromyalgia, particularly within models emphasizing autonomic dysfunction, rehabilitation, and the reciprocal relationship between emotional regulation and chronic pain (Kulshreshtha, 2023). Among patients with burning mouth syndrome, personality patterns differ according to depression history, demonstrating that somatic pain conditions may contain psychologically heterogeneous subgroups even when the presenting physical complaint is similar (Tu et al., 2021). Recent evidence concerning orofacial pain further indicates that pain intensity, sleep quality, sleep bruxism, and personality are interrelated (Orzeszek et al., 2025). These findings are important because they suggest that similar levels of physical discomfort may arise within distinct psychological configurations. Some individuals may experience somatic symptoms in the context of elevated negative emotionality, others in association with impaired emotional awareness, and still others through the combined effects of sleep disruption, poor coping flexibility, and chronic stress. Conventional variable-centered analyses can identify average associations among these factors, but they may obscure meaningful subgroups characterized by different combinations of risk and protection.

Alexithymia constitutes another central component of psychosomatic susceptibility. It is commonly defined by difficulty identifying feelings, difficulty describing emotions, and a cognitive style oriented toward external events rather than internal emotional states. When emotional experiences are poorly differentiated or represented, physiological activation may be interpreted primarily as bodily discomfort rather than as an emotional response. This process may contribute to symptom amplification, delayed help-seeking for psychological distress, and repeated medical consultation for physical complaints. Research among university students has shown a close relationship between personality traits and alexithymia, reinforcing the possibility that emotional-awareness deficits are embedded within broader dispositional patterns (Rahimi et al., 2025). Evidence from medical students similarly indicates that resilience is related to both alexithymia and personality traits, suggesting that emotional awareness may influence whether dispositional vulnerability is translated into maladaptive outcomes (Elagouz et al., 2025). During the COVID-19 pandemic, personality, resilience, and alexithymia jointly contributed to mental health, demonstrating that no single construct adequately explained psychological adjustment under severe collective stress (Osimo et al., 2021). Alexithymia may therefore operate

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both as an independent vulnerability and as a mechanism linking personality to psychosomatic outcomes.

Interoception provides a plausible pathway through which alexithymia and negative emotionality influence somatic symptom severity. Interoception refers to the perception, interpretation, and integration of internal bodily signals. Deficits or distortions in interoceptive processing can produce uncertainty about the meaning of physiological changes and may increase reliance on threat-based interpretations. Shared and distinct interoceptive impairments have been identified in individuals with high alexithymia and high neuroticism, indicating that these constructs overlap but are not interchangeable (Gaggero et al., 2022). A person with high negative emotionality may detect and catastrophically interpret bodily sensations, whereas a person with high alexithymia may experience physiological arousal without being able to identify the underlying emotional state. When both characteristics are elevated, the risk of persistent somatic distress may be especially pronounced. This possibility underscores the importance of examining configurations rather than isolated predictors. It also suggests that psychosomatic susceptibility may involve qualitatively different profiles, including emotionally constrained individuals whose alexithymia is elevated without severe negative affect, affectively reactive individuals who experience bodily symptoms despite relatively intact emotional awareness, and multidimensionally vulnerable individuals who show simultaneous elevations across several risk factors.

Coping flexibility may determine whether personality and emotional-processing vulnerabilities become translated into persistent distress. Coping flexibility involves monitoring whether a coping strategy is effective, abandoning ineffective responses, and selecting alternatives that better match changing situational demands. A person may possess elevated negative emotionality but remain relatively protected when able to modify coping behavior, seek support, regulate routines, and reinterpret stressors. In contrast, rigid coping may prolong physiological arousal and reinforce maladaptive cycles of avoidance, rumination, sleep disturbance, and symptom monitoring. Studies of caregivers demonstrate that personality-based subtypes differ in their value systems and adaptation to demanding care responsibilities (Sołtys & Wnuk, 2025), illustrating the importance of person-centered heterogeneity in stressful contexts. Gender-specific relationships between personality and mental health have also been observed among family members of intensive care patients, suggesting that coping resources and contextual roles may influence how dispositional traits are expressed under acute medical stress (Lu et al., 2024). The consequences of personality are therefore contingent on the regulatory capacities available to the individual. A profile characterized by high negative emotionality but preserved coping flexibility may differ substantially from one in which the same trait is accompanied by alexithymia, rigid coping, and disturbed sleep.

Sleep disturbance is both a potential consequence of psychological vulnerability and a mechanism through which psychosomatic symptoms are intensified. Insufficient or fragmented sleep can impair emotion regulation, increase pain sensitivity, reduce cognitive control, heighten autonomic activation, and lower the threshold for perceiving bodily discomfort. A systematic review of personality and insomnia concluded that personality traits, particularly neuroticism and related negative-affect tendencies, are consistently associated with insomnia symptoms (Akram et al., 2023). Direct and anxiety-mediated associations between personality traits and insomnia further indicate that personality may influence sleep through both immediate dispositional pathways and intermediate emotional processes (Conway et al., 2025). In a nonclinical population, insomnia was related to personality traits and time perspective, showing that disturbed sleep is connected with enduring psychological orientation even outside formally diagnosed sleep disorders (Fabbri et al., 2022). Research among shift workers has likewise demonstrated associations between personality and insomnia symptoms under conditions of circadian disruption (Holzinger et al., 2021). Sleep disturbance may therefore function as an amplifying factor within psychosomatic susceptibility profiles: individuals who combine negative emotionality, alexithymia, and low coping flexibility with poor sleep may be especially likely to report severe bodily symptoms.

Psychosomatic processes also have relevance to chronic medical illness. A psychosomatic framework has been used to reinterpret mechanisms involved in type 2 diabetes mellitus, emphasizing that metabolic disease develops and progresses within a broader network of psychological, behavioral, and social influences (Min et al., 2022). This perspective does not imply that physical disease is psychologically caused; rather, it recognizes that emotional stress, personality, behavior, sleep, and physiological regulation may interact with biomedical mechanisms. Long-term physical and mental health consequences have also been documented following adolescent anabolic steroid use,

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illustrating how behavioral exposure, personality-related motivations, and later health outcomes can become intertwined (Berger et al., 2024). Such findings support the inclusion of both psychological and somatic indicators when examining health susceptibility. They also caution against reducing psychosomatic research to the study of medically unexplained symptoms alone. Psychosomatic vulnerability can coexist with diagnosed physical disease, influence illness severity, and shape the subjective burden associated with objectively verifiable conditions.

Despite substantial evidence linking personality, alexithymia, coping, sleep, and somatic symptoms, most studies have relied on variable-centered methods that estimate the average association between one predictor and one outcome. This approach is useful for testing linear relationships but assumes that the sample is relatively homogeneous. In practice, two individuals with the same level of somatic symptom severity may possess markedly different psychological characteristics and may require different preventive or therapeutic strategies. Unsupervised machine learning provides a person-centered alternative by identifying naturally occurring groups without imposing predefined diagnostic categories. It can simultaneously consider multiple standardized indicators and detect nonlinear or configurational patterns that may not be visible in conventional regression models. The potential value of this approach is reinforced by research showing that personality-health relationships vary across occupational conditions, developmental stages, health contexts, and exposure to adversity (Zhao et al., 2021). Research on medical staff during the second wave of the COVID-19 pandemic, for example, identified interconnected symptoms of depression, anxiety, acute stress, and insomnia, illustrating the clustering of psychological and sleep-related difficulties under sustained pressure (Zhao et al., 2021). The capacity to identify subgroups may therefore improve psychosomatic screening by distinguishing low-risk individuals, emotionally constrained individuals, sleep-related vulnerability, and multidimensional high-risk patterns.

A profile-based approach may also clarify why apparently similar personality traits produce different health consequences across individuals. The expression of negative emotionality may depend on alexithymia, coping adaptability, sleep continuity, resilience, social context, and prior exposure to stress. Personality may function as a broad vulnerability, while alexithymia shapes emotional representation, coping flexibility determines regulatory adaptation, and sleep disturbance magnifies both emotional and somatic reactivity. Research examining psychological well-being, occupational distress, chronic pain, depression, behavioral dysregulation, and stress adaptation collectively suggests that these dimensions operate as a system rather than as isolated variables. Such a system-oriented view is especially appropriate for community samples, in which vulnerability is expected to exist along a continuum and may not correspond to formal psychiatric or medical diagnoses. Identifying empirically derived profiles could support more precise prevention by indicating whether an individual would benefit primarily from emotional-awareness training, coping-flexibility enhancement, sleep-focused intervention, personality-informed stress management, or integrated psychosomatic care.

The aim of this study was to use unsupervised machine learning to identify distinct psychosomatic susceptibility profiles among adults in Ireland based on Big Five personality traits, alexithymia, coping flexibility, sleep disturbance, and somatic symptom severity.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional, person-centered design to identify distinct psychosomatic susceptibility profiles through unsupervised machine learning analysis of Big Five personality traits, alexithymia, coping flexibility, sleep disturbance, and somatic symptom severity. The study population consisted of adults residing in the Republic of Ireland during the data collection period. A total of 713 participants were included in the final analysis. Participants were recruited from the general adult population through community organizations, universities, workplaces, social media advertisements, primary healthcare information networks, and online research participation platforms. Recruitment was conducted across urban, suburban, and rural areas to increase the demographic and socioeconomic diversity of the sample. Eligibility criteria included being at least 18 years of age, currently residing in Ireland, having lived in Ireland for a minimum of 12 months, possessing sufficient English-language proficiency to understand and complete the questionnaires, and providing electronic informed consent. Individuals were excluded when they submitted substantially incomplete questionnaires, failed more than one embedded attention-check item, demonstrated invariant or implausibly rapid response patterns, or provided duplicate responses identified through

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response timestamps and anonymous digital identifiers. Participants were not excluded solely because they reported a physical or psychological health condition, since the purpose of the study was to identify naturally occurring psychosomatic susceptibility patterns in a heterogeneous community sample rather than to examine a narrowly defined clinical population. Data were collected through a secure online survey system, and participants completed all measures independently in a single assessment session requiring approximately 25 to 35 minutes. The questionnaire was configured so that participants could review and modify their responses before final submission, while no directly identifying information was collected. The final sample size was considered adequate for multivariate profile identification because it provided a large ratio of observations to clustering variables, supported the detection of both common and relatively small latent subgroups, and permitted internal validation through repeated resampling and holdout procedures.

2.2. Measures

Data were collected using a demographic and health information form together with five standardized self-report instruments assessing the psychological and somatic domains included in the profile analysis. The demographic and health information form recorded participants' age, gender, educational attainment, employment status, relationship status, area of residence, perceived financial status, history of chronic physical illness, history of diagnosed mental health conditions, current use of psychotropic medication, and engagement with psychological or medical services during the preceding 12 months. These variables were not used as primary clustering indicators because the profiles were intended to emerge from the specified psychological and psychosomatic characteristics; instead, demographic and health variables were used to describe the sample and examine the external characteristics of the resulting profiles. Big Five personality traits were assessed using the 30-item Big Five Inventory–2 Short Form. This instrument measures openness to experience, conscientiousness, extraversion, agreeableness, and negative emotionality, with six items representing each broad personality domain. Participants indicated the extent to which each statement described them on a five-point Likert scale ranging from strongly disagree to strongly agree. Negatively worded items were reverse-scored according to the instrument's scoring protocol, and separate mean scores were calculated for the five personality domains. Higher scores represented stronger expression of the corresponding trait. The short form was selected because it provides broad coverage of the five-factor model while reducing participant burden in a multivariable online assessment. Alexithymia was assessed using the 20-item Toronto Alexithymia Scale. The scale evaluates difficulties in identifying feelings, difficulties in describing feelings, and externally oriented thinking. Items are rated on a five-point scale ranging from strongly disagree to strongly agree. After reverse-scoring the relevant items, responses are summed to generate a total alexithymia score, with higher scores indicating greater difficulty recognizing, differentiating, and verbally communicating emotional experiences. The total score was used as the principal alexithymia indicator in the clustering analysis because the study focused on the overall contribution of impaired emotional awareness to psychosomatic susceptibility. Subscale scores were retained for supplementary characterization of the identified profiles.

Coping flexibility was evaluated using the Coping Flexibility Scale, a 10-item self-report measure designed to assess the ability to discontinue ineffective coping strategies and generate or implement alternative responses when situational demands change. The instrument comprises evaluation coping and adaptive coping components. Evaluation coping reflects the individual's capacity to monitor the effectiveness of an ongoing coping response and abandon it when it is no longer useful, whereas adaptive coping reflects the ability to develop and employ alternative coping strategies. Participants rated each item on a four-point response scale. Relevant items were scored in accordance with the original scoring instructions, and a total coping flexibility score was calculated, with higher scores reflecting greater capacity to modify coping behavior in response to changing stressors. Sleep disturbance was measured using the Pittsburgh Sleep Quality Index, which assesses subjective sleep quality during the previous month. The instrument contains 19 self-rated items that are combined into seven component scores covering subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. Each component is scored from zero to three, and the component scores are summed to produce a global score ranging from zero to 21. Higher global scores indicate poorer sleep quality and more severe sleep-related disturbance. The global score was entered into the profile analysis because it captures the cumulative burden of

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multiple sleep problems that may contribute to emotional dysregulation, physiological arousal, fatigue, pain sensitivity, and heightened awareness of bodily sensations. Somatic symptom severity was assessed using the 15-item Patient Health Questionnaire. The instrument evaluates the extent to which participants were bothered by common physical symptoms during the preceding four weeks, including fatigue, pain, gastrointestinal complaints, dizziness, cardiopulmonary sensations, and sleep-related problems. Each symptom is rated as not bothered at all, bothered a little, or bothered a lot, corresponding to scores of zero, one, and two. Item scores are summed to generate a total score ranging from zero to 30, with higher values indicating greater somatic symptom burden. The questionnaire was used as a dimensional measure rather than as an independent diagnostic instrument. For the item concerning menstrual difficulties, the standard scoring procedure was applied, and the denominator was not altered for participants for whom the item was not applicable. Internal consistency was evaluated separately for every multi-item instrument and subscale using Cronbach's alpha and McDonald's omega. Scale scores were calculated only when participants had answered at least 80% of the items belonging to the relevant measure. When this criterion was met, an individual's mean response to the completed items within the scale was used to replace the limited number of missing item responses before the total or mean score was calculated. Higher scores consistently represented greater levels of the construct named by the scale, except for coping flexibility, for which higher scores represented a more adaptive psychological capacity.

2.3. Data Analysis

Data analysis was conducted using a combination of conventional statistical procedures and unsupervised machine learning techniques. Initial data screening included verification of response completeness, identification of duplicate submissions, assessment of attention-check performance, inspection of completion times, and detection of invariant or mechanically patterned responses. Descriptive statistics were calculated for all demographic, psychological, sleep-related, and somatic variables. Continuous variables were summarized using means, standard deviations, medians, interquartile ranges, minimums, maximums, skewness, and kurtosis, while categorical variables were summarized using frequencies and percentages. The pattern and proportion of missing data were examined before the profile analysis. When missingness at the scale-score level was below 5% and was compatible with a missing-at-random mechanism, missing values were estimated through multiple imputation using predictive mean matching. Participants with extensive missing data or insufficient responses for calculating multiple core study variables were excluded before imputation. Potential multivariate outliers were examined using robust Mahalanobis distances and isolation-based anomaly detection. Cases identified as potentially unusual were individually inspected and were removed only when they reflected implausible, inconsistent, or low-quality responses; valid extreme observations were retained to preserve genuine individual variation in psychosomatic susceptibility. The variables entered into the primary clustering analysis were openness to experience, conscientiousness, extraversion, agreeableness, negative emotionality, total alexithymia, total coping flexibility, global sleep disturbance, and total somatic symptom severity. Because these variables were measured on different numerical scales, each indicator was transformed into a standardized z score with a mean of zero and a standard deviation of one. The distributions were inspected for severe skewness, and robust scaling based on medians and interquartile ranges was used in sensitivity analyses to ensure that the identified profiles were not artifacts of non-normal distributions or extreme scores. Multicollinearity was examined through Pearson correlation coefficients and variance inflation factors. Highly redundant variables were not entered simultaneously when their inclusion would have caused one construct to exert disproportionate influence on distance calculations.

Before clustering, the suitability of the data for meaningful subgroup identification was assessed using the Hopkins statistic, visual inspection of pairwise distance patterns, and comparison of the observed data with randomly generated reference datasets. Several unsupervised learning algorithms were evaluated rather than relying on a single clustering method. Candidate solutions were generated using k-means clustering, partitioning around medoids, Gaussian mixture modeling, and agglomerative hierarchical clustering with Ward's linkage and Euclidean distance. Solutions containing between two and six profiles were examined because this range was sufficiently broad to detect clinically meaningful heterogeneity while limiting the creation of very small or unstable subgroups. The optimal number of profiles was determined by integrating multiple statistical criteria, including average silhouette width, the Calinski–Harabasz index, the Davies–Bouldin index, the gap statistic, within-cluster sum of squares, and, for Gaussian mixture models, the Bayesian information criterion. No solution was selected on the basis of a single index. Preference was given to a solution that demonstrated strong internal separation, acceptable within-profile homogeneity, theoretical interpretability, adequate profile sizes, and reproducibility across clustering algorithms. Cluster stability was evaluated through 1,000 bootstrap resamples. For each resample, the clustering procedure was repeated, and the similarity between the original and resampled solutions was quantified using Jaccard similarity coefficients and the adjusted Rand index. A random 20% holdout subsample was additionally used to examine whether profile centroids and participant classifications could be reproduced in data that had not directly determined the primary solution. Agreement between the primary and holdout classifications was assessed using centroid similarity, adjusted Rand indices, and profile-specific classification consistency.

The final profiles were interpreted by examining standardized means and 95% confidence intervals for all clustering indicators. Profile labels were assigned only after completion of the machine learning analysis and were based on the overall configuration of personality, alexithymia, coping flexibility, sleep disturbance, and somatic symptom severity rather than on a single elevated variable. Principal component analysis and uniform manifold approximation and projection were used exclusively to visualize the multivariate structure and separation of the profiles in two-dimensional space; these dimensionality-reduction procedures were not used as substitutes for the primary clustering algorithms. Differences among the identified profiles in demographic and health-related characteristics were examined to provide external validation. Continuous variables were compared using analysis of variance when distributional assumptions were satisfied and Welch's analysis of variance when homogeneity of variance was violated. Kruskal–Wallis tests were used for markedly non-normal variables that remained unsuitable for parametric analysis after inspection. Significant omnibus comparisons were followed by adjusted pairwise tests. Categorical variables were compared using chi-square tests or Fisher's exact tests when expected cell frequencies were small. Effect sizes were reported using partial eta squared or omega squared for continuous comparisons and Cramér's V for categorical comparisons. Multinomial logistic regression was conducted as a supplementary analysis to examine whether age, gender, educational attainment, employment status, chronic illness, and mental health history were independently associated with profile membership. These demographic and health variables were not used to generate the profiles and therefore served only as external correlates. Sensitivity analyses repeated the clustering procedure after excluding participants who reported a diagnosed chronic medical condition, after excluding participants currently using psychotropic medication, and after replacing total alexithymia and coping flexibility scores with their respective subscale scores. The similarity of alternative solutions to the primary profile structure was evaluated using the adjusted Rand index. Statistical tests were two-tailed, and the significance level was set at .05. False discovery rate correction was applied to families of post hoc comparisons to reduce the probability of type I error arising from multiple testing.

3. Findings and Results

The final analytical sample consisted of 713 adults residing in the Republic of Ireland. Participants ranged in age from 18 to 74 years, with a mean age of 38.74 years and a standard deviation of 12.46 years. Of the participants, 415 were women (58.2%), 284 were men (39.8%), and 14 identified as nonbinary or reported another gender identity (2.0%). Regarding relationship status, 317 participants were married or cohabiting (44.5%), 299 were single and had never married (41.9%), and 97 were separated, divorced, or widowed (13.6%). A total of 183 participants had completed secondary education or below (25.7%), 310 held an undergraduate qualification (43.5%), and 220 held a postgraduate qualification (30.9%). In relation to employment, 449 participants were employed either full-time or part-time (63.0%), 105 were students (14.7%), 72 were unemployed or seeking employment (10.1%), and 87 were retired, engaged in unpaid caregiving, or unable to work (12.2%). Most participants lived in urban or suburban areas, including 318 participants from major urban centers (44.6%) and 241 from suburban or smaller urban areas (33.8%), while 154 participants lived in rural communities (21.6%). A physician-diagnosed chronic physical health condition was reported by 209 participants (29.3%), whereas 188 participants reported a previous or current diagnosed mental health condition (26.4%). Current use of psychotropic medication was reported by 111 participants (15.6%), and 164 participants had received psychological or psychiatric services during the preceding 12 months (23.0%). There were no statistically significant differences

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between participants retained in the final analysis and those excluded because of incomplete or low-quality responses with regard to age or gender distribution, suggesting that the final analytical sample was not substantially affected by systematic demographic attrition.

Table 1

Descriptive Statistics, Internal Consistency Coefficients, and Correlations Among the Clustering Variables

Variable	Mean	SD	Observed Range	Cronbach's α	McDonald's ω	1	2	3	4	5	6	7	8	9
1	3.63	0.62	1.50–5.00	.78	.79	—								
2	3.48	0.68	1.17–5.00	.82	.83	.16***	—							
3	3.29	0.74	1.00–5.00	.81	.82	.22***	.19***	—						
4	3.72	0.61	1.50–5.00	.76	.77	.18***	.23***	.17***	—					
5	3.10	0.77	1.00–5.00	.84	.85	−.12**	−.31***	−.35***	−.20***	—				
6	51.84	12.38	22–88	.88	.89	−.18***	−.24***	−.29***	−.21***	.40***	—			
7	18.91	5.21	3–30	.86	.87	.25***	.37***	.32***	.25***	−.44***	−.41***	—		
8	7.46	3.82	0–19	.83	.84	−.10**	−.29***	−.24***	−.16***	.52***	.38***	−.39***	—	
9	8.91	5.23	0–27	.87	.88	−.08*	−.23***	−.20***						

1. Openness to experience; 2. Conscientiousness; 3. Extraversion; 4. Agreeableness; 5. Negative emotionality; 6. Alexithymia; 7. Coping flexibility; 8. Sleep disturbance; 9. Somatic symptom severity

As shown in Table 1, all study instruments demonstrated acceptable to strong internal consistency. Cronbach's alpha coefficients ranged from .76 for agreeableness to .88 for alexithymia, while McDonald's omega coefficients ranged from .77 to .89. These findings indicated that the measures provided sufficiently reliable scores for inclusion in the unsupervised machine learning analysis. The mean global sleep disturbance score was 7.46, indicating that sleep-related difficulties were relatively common in the sample, while the mean somatic symptom severity score of 8.91 suggested a generally mild-to-moderate level of physical symptom burden. The mean alexithymia score was 51.84, although the broad observed range indicated substantial variation in participants' ability to identify and communicate emotional experiences. Coping flexibility also varied considerably, supporting its potential value in distinguishing subgroups with different psychosomatic susceptibility patterns. The correlation matrix demonstrated theoretically coherent associations among the study variables without indicating problematic redundancy. Negative emotionality was positively associated with alexithymia, sleep disturbance, and somatic symptom severity and negatively associated with coping flexibility. Its strongest correlations were with somatic symptom severity, $r = .55$, $p < .001$, and sleep disturbance, $r = .52$, $p < .001$. Sleep disturbance was also strongly associated with somatic symptom severity, $r = .58$, $p < .001$, suggesting that participants with greater sleep-related impairment tended to report a higher burden of bodily symptoms. Alexithymia was positively associated with somatic symptom severity, $r = .43$, $p < .001$, and sleep disturbance, $r = .38$, $p < .001$, while it was inversely associated with coping flexibility, $r = −.41$, $p < .001$. Conscientiousness, extraversion, and agreeableness were each negatively related to negative emotionality, alexithymia, sleep disturbance, and somatic symptom severity and positively related to coping flexibility. Openness showed weaker associations with the psychosomatic variables than the other personality dimensions. The largest correlation was below .60, indicating that the clustering indicators represented related but empirically distinguishable dimensions and could be retained simultaneously without excessive multicollinearity.

Table 2

Comparison of Candidate Cluster Solutions and Stability Indices

Number of Profiles	Average Silhouette Width	Calinski–Harabasz Index	Davies–Bouldin Index	Gap Statistic	Smallest Profile, n (%)	Mean Bootstrap Jaccard Coefficient	Holdout Adjusted Rand Index
2	.321	221.64	1.46	.38	274 (38.4)	.86	.73
3	.356	244.81	1.24	.44	155 (21.7)	.83	.76
4	.402	271.33	1.03	.51	106 (14.9)	.88	.82
5	.371	259.02	1.12	.49	58 (8.1)	.74	.69
6	.343	247.48	1.21	.47	40 (5.6)	.68	.61

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Preliminary assessment supported the presence of a meaningful cluster structure in the data. The Hopkins statistic was .78, which was substantially above the value expected for uniformly distributed observations and indicated that the multivariate data were suitable for clustering. Candidate solutions containing two through six profiles were subsequently evaluated. As reported in Table 2, the four-profile solution produced the highest average silhouette width, the highest Calinski–Harabasz index, the highest gap statistic, and the lowest Davies–Bouldin index. It therefore provided the strongest overall balance between within-profile cohesion and between-profile separation. The four-profile solution also retained an adequately sized smallest subgroup, consisting of 106 participants or 14.9% of the sample. By comparison, the five- and six-profile solutions generated smaller subgroups and showed reductions in bootstrap stability and holdout reproducibility.

The four-profile solution demonstrated strong stability across 1,000 bootstrap samples, with a mean Jaccard similarity coefficient of .88. Profile-specific Jaccard coefficients ranged from .84 to .92, indicating that each subgroup was consistently reproduced across resampled datasets. Classification in the 20% holdout sample showed substantial agreement with the primary solution, as reflected by an adjusted Rand index of .82. The same general four-profile structure was identified through partitioning around medoids and agglomerative hierarchical clustering. Agreement between the primary k-means solution and the partitioning around medoids solution was .79, while agreement with the hierarchical clustering solution was .76. Gaussian mixture modeling also supported a four-component solution based on the Bayesian information criterion, although its classification agreement with the k-means solution was moderately lower at .71. Collectively, these findings indicated that the four-profile structure was not dependent on one specific clustering algorithm and was sufficiently stable for substantive interpretation.

Table 3

Standardized Mean Scores and Omnibus Comparisons Across the Four Psychosomatic Susceptibility Profiles

Clustering Indicator	Resilient–Low Susceptibility, n = 230 (32.3%)	Emotionally Constrained, n = 154 (21.6%)	Sleep-Disturbed Negative Affect, n = 223 (31.3%)	Multidimensional High Susceptibility, n = 106 (14.9%)	F(3, 709)	p	Partial η²
Openness to experience	0.36[a]	−0.44[c]	0.06[b]	−0.24[c]	48.72	<.001	.171
Conscientiousness	0.67[a]	0.07[b]	−0.33[c]	−0.83[d]	146.38	<.001	.383
Extraversion	0.56[a]	−0.54[c]	−0.04[b]	−0.34[c]	109.61	<.001	.317
Agreeableness	0.35[a]	−0.15[b]	0.05[b]	−0.65[c]	61.44	<.001	.207
Negative emotionality	−0.89[d]	−0.09[c]	0.51[b]	1.01[a]	318.57	<.001	.574
Alexithymia	−0.82[d]	0.78[b]	−0.22[c]	1.08[a]	283.12	<.001	.545
Coping flexibility	0.83[a]	−0.17[b]	−0.27[b]	−0.97[c]	271.40	<.001	.535
Sleep disturbance	−0.90[d]	−0.20[c]	0.60[b]	1.00[a]	301.66	<.001	.561
Somatic symptom severity	−0.90[d]	0.00[c]	0.40[b]	1.10[a]	344.79	<.001	.593

The four profiles differed significantly across all nine clustering indicators, as shown in Table 3. The largest between-profile difference was observed for somatic symptom severity, $F(3, 709) = 344.79$, $p < .001$, partial $\eta^2 = .593$, indicating that approximately 59.3% of the variance in somatic symptom scores was associated with profile membership. The multidimensional high-susceptibility profile displayed the highest standardized somatic symptom score, whereas the resilient–low-susceptibility profile displayed the lowest score. The sleep-disturbed negative-affect profile also reported significantly greater somatic symptom severity than the emotionally constrained profile, confirming that elevated sleep disturbance and negative emotionality were accompanied by a clinically meaningful increase in bodily symptom burden.

Negative emotionality also showed a large profile effect, $F(3, 709) = 318.57$, $p < .001$, partial $\eta^2 = .574$. Participants in the multidimensional high-susceptibility profile scored approximately one standard deviation above the sample mean, while those in the resilient–low-susceptibility profile scored nearly one standard deviation below it. The sleep-disturbed negative-affect profile showed moderately elevated negative emotionality, whereas the emotionally constrained profile remained close to the overall sample mean. All pairwise differences in negative emotionality were statistically significant after false discovery rate correction.

Sleep disturbance differed similarly across all profiles, $F(3, 709) = 301.66$, $p < .001$, partial $\eta^2 = .561$. The multidimensional high-susceptibility and sleep-disturbed negative-affect profiles reported the most severe sleep problems, although the former profile was significantly more impaired. In contrast, the resilient–low-susceptibility profile reported substantially lower sleep disturbance than every other subgroup.

A large difference was also found for alexithymia, $F(3, 709) = 283.12$, $p < .001$, partial $\eta^2 = .545$. Alexithymia was highest in the multidimensional high-susceptibility profile, followed by the emotionally constrained profile. The emotionally constrained profile therefore appeared to represent a distinct form of psychosomatic susceptibility in which difficulty identifying and verbalizing emotional states was prominent despite the absence of markedly elevated negative emotionality or somatic symptom severity. Participants in the resilient–low-susceptibility profile reported the lowest alexithymia scores. The sleep-disturbed negative-affect profile also scored below the sample mean, further differentiating its emotional-reactivity and sleep-related pattern from the emotionally constrained pattern.

Coping flexibility showed a substantial profile effect, $F(3, 709) = 271.40$, $p < .001$, partial $\eta^2 = .535$. The resilient–low-susceptibility profile demonstrated the greatest ability to evaluate the effectiveness of coping responses and replace ineffective strategies. The multidimensional high-susceptibility profile showed the lowest coping flexibility, with a standardized mean almost one standard deviation below the sample average. The emotionally constrained and sleep-disturbed negative-affect profiles did not differ significantly from each other in coping flexibility, although both scored significantly below the resilient profile and significantly above the multidimensional high-susceptibility profile. This pattern suggested that severely restricted coping adaptability was particularly characteristic of participants who simultaneously experienced high negative emotionality, alexithymia, sleep disturbance, and somatic symptom severity.

Significant differences were additionally observed across all Big Five personality dimensions. Conscientiousness showed the strongest personality-based distinction, $F(3, 709) = 146.38$, $p < .001$, partial $\eta^2 = .383$. The resilient–low-susceptibility profile demonstrated the highest conscientiousness, followed by the emotionally constrained, sleep-disturbed negative-affect, and multidimensional high-susceptibility profiles. Extraversion also differed substantially, $F(3, 709) = 109.61$, $p < .001$, partial $\eta^2 = .317$, with the resilient profile scoring significantly higher than the remaining groups. The emotionally constrained and multidimensional high-susceptibility profiles were both characterized by below-average extraversion, although their scores did not differ significantly from each other after adjustment for multiple comparisons. Agreeableness differed significantly across profiles, $F(3, 709) = 61.44$, $p < .001$, partial $\eta^2 = .207$, and was especially low in the multidimensional high-susceptibility profile. Openness produced the smallest, although still substantial, profile effect, $F(3, 709) = 48.72$, $p < .001$, partial $\eta^2 = .171$. Openness was highest in the resilient profile and lowest in the emotionally constrained profile.

External validation analyses further demonstrated that profile membership was meaningfully associated with participants' health characteristics. A diagnosed chronic physical condition was reported by 17.8% of participants in the resilient–low-susceptibility profile, 24.0% in the emotionally constrained profile, 34.5% in the sleep-disturbed negative-affect profile, and 50.9% in the multidimensional high-susceptibility profile, $\chi^2(3) = 50.84$, $p < .001$, Cramér's V = .267. A diagnosed mental health condition was reported by 13.5%, 24.7%, 30.0%, and 47.2% of the four profiles, respectively, $\chi^2(3) = 50.37$, $p < .001$, Cramér's V = .266. Current psychotropic medication use was also most common in the multidimensional high-susceptibility profile, affecting 30.2% of that group compared with 7.4% of the resilient profile, 13.0% of the emotionally constrained profile, and 18.8% of the sleep-disturbed negative-affect profile, $\chi^2(3) = 31.58$, $p < .001$, Cramér's V = .210.

In supplementary multinomial logistic regression analysis, the resilient–low-susceptibility profile was used as the reference category. After adjustment for age, gender, education, employment, and relationship status, participants with a chronic physical health condition had higher odds of membership in the sleep-disturbed negative-affect profile, adjusted odds ratio = 2.04, 95% confidence interval [1.32, 3.15], $p = .001$, and the multidimensional high-susceptibility profile, adjusted odds ratio = 3.71, 95% confidence interval [2.23, 6.19], $p < .001$. A history of diagnosed mental health conditions was independently associated with the emotionally constrained profile, adjusted odds ratio = 1.88, 95% confidence interval [1.14, 3.10], $p = .014$, the sleep-disturbed negative-affect profile, adjusted odds ratio = 2.31, 95% confidence interval [1.47, 3.64], $p < .001$, and the multidimensional high-susceptibility profile, adjusted odds ratio = 4.18, 95% confidence interval [2.46, 7.11], $p < .001$.

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Age was weakly associated with membership in the sleep-disturbed negative-affect profile but was not independently associated with multidimensional high susceptibility after health conditions were controlled. Gender, educational attainment, employment status, and relationship status did not consistently predict profile membership across the adjusted models.

The primary four-profile structure remained stable in the sensitivity analyses. Repeating the clustering procedure after excluding participants with chronic physical illnesses produced an adjusted Rand index of .81 in comparison with the original solution. Excluding participants currently using psychotropic medication produced an adjusted Rand index of .84. When the total alexithymia and coping flexibility scores were replaced by their respective subscale scores, a substantively equivalent four-profile structure emerged, with an adjusted Rand index of .78. The resilient and multidimensional high-susceptibility profiles were especially stable across all alternative specifications, while a small number of participants shifted between the emotionally constrained and sleep-disturbed negative-affect profiles. These findings indicated that the identified psychosomatic susceptibility profiles were not primarily attributable to diagnosed illness, medication use, the scoring structure of the measures, or a limited number of influential observations.

Figure 1

Standardized Mean Scores for the Four Psychosomatic Susceptibility Profiles Across the Nine Clustering Indicators

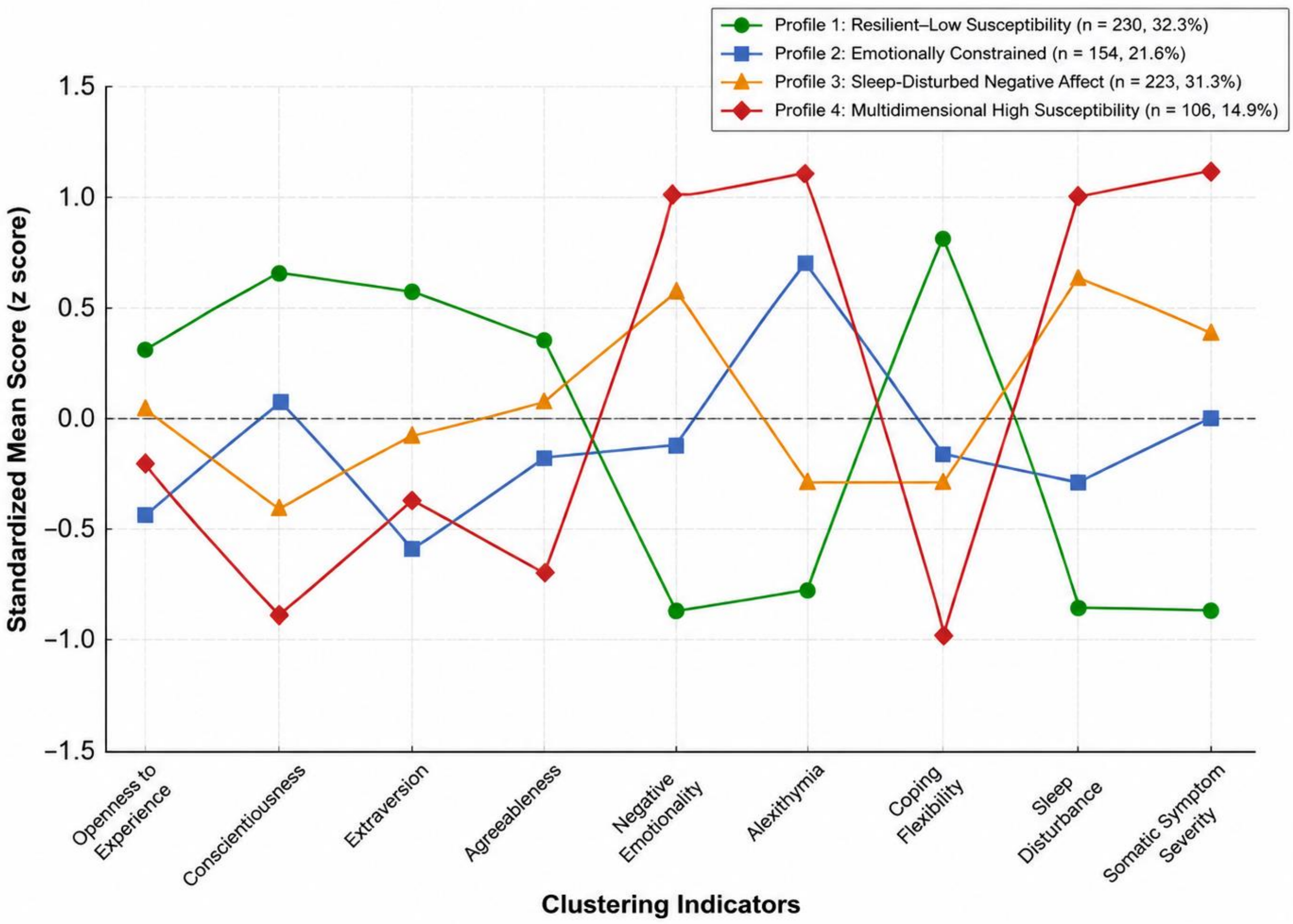

Figure 1 displays the standardized mean pattern of Big Five personality traits, alexithymia, coping flexibility, sleep disturbance, and somatic symptom severity across the four identified profiles. The first profile was characterized by scores above the sample mean for openness, conscientiousness, extraversion, agreeableness, and coping flexibility, together with markedly below-average scores for negative emotionality, alexithymia, sleep disturbance, and somatic symptom severity. This configuration represented the most psychologically adaptive pattern and was therefore

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labeled the resilient–low-susceptibility profile. The second profile was distinguished primarily by elevated alexithymia and reduced extraversion and openness, while negative emotionality, sleep disturbance, and somatic symptom severity remained close to the sample mean. This subgroup was labeled the emotionally constrained profile, reflecting its prominent difficulty with emotional identification and expression in the absence of broadly elevated psychosomatic symptoms. The third profile demonstrated elevated negative emotionality, sleep disturbance, and somatic symptom severity, accompanied by moderately low conscientiousness and coping flexibility. Alexithymia was slightly below the sample mean in this profile, suggesting that its psychosomatic vulnerability was more strongly connected with emotional reactivity and sleep impairment than with restricted emotional awareness. This subgroup was labeled the sleep-disturbed negative-affect profile. The fourth profile showed the most pronounced risk configuration, including highly elevated negative emotionality, alexithymia, sleep disturbance, and somatic symptom severity, together with markedly reduced conscientiousness, agreeableness, and coping flexibility. It was consequently labeled the multidimensional high-susceptibility profile. Visual inspection showed clear differences in the shape and elevation of the four profile trajectories, particularly for negative emotionality, alexithymia, coping flexibility, sleep disturbance, and somatic symptom severity.

4. Discussion and Conclusion

The present study used unsupervised machine learning to identify psychosomatic susceptibility profiles based on Big Five personality traits, alexithymia, coping flexibility, sleep disturbance, and somatic symptom severity among adults residing in Ireland. The analysis supported a stable four-profile solution consisting of a resilient–low-susceptibility profile, an emotionally constrained profile, a sleep-disturbed negative-affect profile, and a multidimensional high-susceptibility profile. The profiles differed significantly across all clustering indicators, with the largest between-profile effects observed for somatic symptom severity, negative emotionality, sleep disturbance, alexithymia, and coping flexibility. The multidimensional high-susceptibility profile exhibited the greatest psychosomatic burden, whereas the resilient–low-susceptibility profile demonstrated the most adaptive configuration. The emotionally constrained and sleep-disturbed negative-affect profiles represented two intermediate but qualitatively distinct patterns, indicating that psychosomatic susceptibility cannot be adequately described along a single low-to-high continuum. The robustness of the four-profile structure across alternative clustering algorithms, bootstrap resampling, holdout validation, and sensitivity analyses further suggested that the identified configurations represented meaningful patterns rather than statistical artifacts. These findings are consistent with biopsychosocial perspectives according to which physical symptoms, emotional functioning, personality, coping, and health behavior interact dynamically rather than functioning as independent determinants of health (Pilafas & Lyrakos, 2021). They also support multidimensional models showing that stress-related health outcomes are embedded within biological, psychological, occupational, social, and cultural systems (Listopad et al., 2021).

The resilient–low-susceptibility profile was the largest subgroup and was characterized by high conscientiousness, extraversion, agreeableness, openness, and coping flexibility, together with low negative emotionality, alexithymia, sleep disturbance, and somatic symptom severity. This pattern suggests that psychosomatic resilience is not defined merely by the absence of distress but by the simultaneous presence of several protective psychological capacities. High conscientiousness may support stable routines, treatment adherence, health-promoting behavior, and effective self-regulation, while extraversion and agreeableness may facilitate social engagement and access to interpersonal support. Openness may contribute to flexible interpretation of stressors and willingness to adopt alternative coping strategies. Recent evidence linking Big Five traits with lifestyle behaviors supports the proposition that personality contributes to health partly through daily routines and behavioral choices (Fukuti et al., 2026). The broader literature similarly conceptualizes personality as an important determinant of emotional adjustment, health risk, and resilience (Williams & Carlson, 2025). The high coping flexibility observed in this profile may have allowed participants to evaluate stressful situations more accurately, discontinue ineffective strategies, and adopt responses better suited to changing demands. Positive personality characteristics have also been associated with resilience and health promotion across generations (Ranjbari, 2021). The present findings therefore suggest that psychosomatic resilience emerges from a coordinated configuration of emotional stability, behavioral regulation, social orientation, and flexible coping rather than from any single protective trait.

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The low negative emotionality observed in the resilient profile was especially important because negative emotionality showed one of the strongest effects across the four groups. Individuals low in negative emotionality are generally less prone to persistent worry, threat sensitivity, irritability, and catastrophic interpretations of internal or external events. Consequently, they may experience lower physiological arousal and may be less likely to interpret ordinary bodily sensations as evidence of illness. Previous work has demonstrated that personality traits contribute to psychological well-being among university populations (Orrù et al., 2025), while research conducted during pandemic restrictions showed that personality influenced how individuals experienced and managed sustained stress (Chauhan & Kumar, 2022). Preliminary findings among adolescents have likewise linked temperament and personality with multifactorial stress reactivity (Ecker et al., 2025). The present results extend these observations by showing that low negative emotionality becomes especially protective when accompanied by low alexithymia, preserved sleep, and high coping flexibility. The combination of these characteristics may reduce both the generation of physiological stress responses and the misinterpretation of bodily signals.

The emotionally constrained profile was characterized by elevated alexithymia, reduced extraversion and openness, and moderately diminished coping flexibility, while negative emotionality, sleep disturbance, and somatic symptom severity remained near the sample average. This configuration is theoretically important because it indicates that difficulty identifying and describing emotions does not invariably coexist with severe psychological distress or extensive somatic complaints. Rather, alexithymia may represent a distinct vulnerability that precedes more overt psychosomatic impairment. Previous research has shown meaningful associations between personality traits and alexithymia among university students (Rahimi et al., 2025). Evidence among medical students has also linked alexithymia and personality traits with resilience, suggesting that emotional-processing difficulties may weaken adaptation even when clinical symptoms are not yet severe (Elagouz et al., 2025). The reduced extraversion observed in this profile may limit emotional disclosure and interpersonal support, while lower openness may restrict exploration of complex internal experiences. During the COVID-19 pandemic, personality, resilience, and alexithymia jointly predicted mental health outcomes, reinforcing the view that alexithymia should be interpreted within a broader dispositional context (Osimo et al., 2021). The emotionally constrained profile may therefore represent a group at risk of internalizing stress physiologically because emotions are insufficiently recognized, symbolized, or communicated.

The distinctiveness of the emotionally constrained profile may also be explained through interoceptive processing. Alexithymia is associated with difficulty interpreting internal bodily and emotional signals, potentially causing physiological arousal to be experienced as undifferentiated discomfort rather than as a recognizable emotional state. Shared and unique interoceptive deficits have been observed in individuals with elevated alexithymia and neuroticism (Gaggero et al., 2022). In the present study, however, alexithymia was elevated in the emotionally constrained group without a corresponding increase in negative emotionality. This finding supports the argument that alexithymia and negative emotionality are related but separable pathways to psychosomatic susceptibility. Individuals in this profile may not report intense anxiety or negative affect, yet they may have difficulty understanding the emotional meaning of tension, fatigue, autonomic activation, or pain. Over time, this limited emotional differentiation may increase vulnerability to somatic symptom escalation, particularly under prolonged stress or deteriorating sleep. The relatively average somatic symptom severity of this group should therefore not be interpreted as an absence of risk, but as evidence of a potentially preclinical or latent vulnerability pattern.

The sleep-disturbed negative-affect profile exhibited elevated negative emotionality, sleep disturbance, and somatic symptom severity, together with reduced conscientiousness and coping flexibility. In contrast to the emotionally constrained profile, alexithymia was not markedly elevated, indicating that members of this group were not primarily characterized by impaired emotional identification. Their susceptibility appeared more closely related to heightened emotional reactivity, sleep impairment, and reduced regulatory capacity. This pattern aligns with extensive evidence linking personality, especially neuroticism or negative emotionality, with insomnia. A systematic review concluded that neuroticism is the personality characteristic most consistently associated with insomnia symptoms (Akram et al., 2023). Direct and anxiety-mediated relationships between personality and insomnia have also been identified, indicating that negative emotionality may influence sleep both directly and through persistent anxiety (Conway et al., 2025). Research in nonclinical populations has similarly found associations

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among insomnia, personality traits, and temporal orientation (Fabbri et al., 2022), while studies of shift workers have demonstrated that personality-related susceptibility remains relevant under conditions of circadian disruption (Holzinger et al., 2021). The current profile therefore appears to reflect a reciprocal cycle in which negative affect disrupts sleep, poor sleep weakens emotional regulation, and both processes intensify the perception and persistence of physical symptoms.

The elevated somatic symptom burden in the sleep-disturbed negative-affect profile is also consistent with research connecting pain, sleep quality, and personality. Among individuals reporting orofacial pain, poorer sleep and personality characteristics were associated with the clinical experience of pain (Orzeszek et al., 2025). A systematic review and meta-analysis of chronic headache similarly identified meaningful relationships between personality and persistent headache conditions (Bottiroli et al., 2023). Personality has also been proposed as a clinically relevant marker in fibromyalgia, particularly in models emphasizing autonomic dysregulation and rehabilitation (Kulshreshtha, 2023). These studies support the possibility that heightened negative emotionality and disturbed sleep lower pain thresholds, increase vigilance toward bodily sensations, and interfere with physiological recovery. The personality differences observed among patients with burning mouth syndrome according to depression history further indicate that similar pain presentations may develop within different psychological contexts (Tu et al., 2021). In the present study, the sleep-disturbed negative-affect profile may therefore reflect a pathway to psychosomatic symptoms driven primarily by hyperarousal and impaired restorative sleep rather than by emotional unawareness.

The multidimensional high-susceptibility profile displayed the most severe and comprehensive vulnerability pattern. Participants in this group showed very high negative emotionality, alexithymia, sleep disturbance, and somatic symptom severity, as well as markedly low coping flexibility, conscientiousness, agreeableness, and extraversion. This profile accounted for a smaller but clinically important segment of the sample and had the highest prevalence of chronic physical conditions, diagnosed mental health conditions, psychotropic medication use, and recent psychological or psychiatric service utilization. The convergence of multiple vulnerabilities suggests a cumulative or synergistic process in which personality-related emotional instability, limited emotional awareness, rigid coping, and sleep impairment reinforce one another. Research on personality and major depressive disorder has demonstrated that personality traits and coping styles possess combined diagnostic and predictive value (Ho et al., 2022). Big Five traits have also been linked with depression and suicidal behavior, especially when negative emotionality is elevated and protective traits are reduced (Chen & Huang, 2024). Reviews of childhood abuse, personality, and depression indicate that long-term vulnerability may arise through the interaction of adverse experiences and enduring personality patterns (Luo & Zhong, 2025). Although adverse childhood experiences were not directly assessed in the present study, the profile's broad impairment is compatible with developmental models in which longstanding emotional and regulatory vulnerabilities become consolidated over time.

Low coping flexibility may have been a central maintaining mechanism within the multidimensional high-susceptibility profile. Individuals who cannot effectively evaluate and modify coping strategies may persist with avoidance, rumination, withdrawal, reassurance seeking, or symptom-focused monitoring even when these responses worsen distress. The importance of context-dependent personality expression has been demonstrated among caregivers of individuals with Alzheimer's disease, where personality and value systems contributed to distinct caregiver types (Sołtys & Wnuk, 2025). Gender-specific associations between personality and mental health have also been found among family members of intensive care patients, highlighting the interaction between dispositional characteristics and situational demands (Lu et al., 2024). Similarly, occupational stress and job demands interact with personality in predicting mental health among police officers (Esther & Obosi, 2023), and personality can modify the relationship between work organization and psychological distress (Parent-Lamarche et al., 2021). These studies support the interpretation that the multidimensional high-susceptibility profile may become especially maladaptive when individuals encounter chronic, uncontrollable, or socially complex stressors. Low coping flexibility may prevent adjustment to such demands, thereby sustaining autonomic arousal, sleep disruption, and somatic distress.

The strong association between profile membership and chronic physical illness reinforces the relevance of psychosomatic frameworks beyond psychiatric symptoms. A psychosomatic interpretation of type 2 diabetes mellitus has emphasized the interaction of biological, psychological, behavioral, and social mechanisms in disease progression (Min et al., 2022). Long-term physical and mental health

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consequences associated with adolescent anabolic steroid use similarly demonstrate how behavior, psychological characteristics, and biomedical outcomes can become interconnected across time (Berger et al., 2024). These findings do not imply that physical disorders are caused solely by personality or emotional processes. Rather, they suggest that psychological characteristics may influence symptom severity, illness management, sleep, treatment adherence, and subjective health burden. The multidimensional high-susceptibility profile may therefore represent individuals for whom physical illness and psychological vulnerability operate reciprocally, with each domain increasing the burden of the other.

The identification of distinct profiles also has implications for understanding broader forms of maladaptive behavior. Systematic evidence concerning gaming disorder has demonstrated the contribution of interacting biopsychosocial factors, including personality and coping characteristics (Chang et al., 2023). Personality and psychopathological symptoms have also been associated with problematic smartphone use across different age groups (Wickord & Quaiser-Pohl, 2022). These behaviors can disrupt sleep, reduce physical activity, intensify social withdrawal, and reinforce emotional avoidance, thereby potentially increasing psychosomatic susceptibility. Time perspective, personality, and morningness have similarly been associated with psychological well-being during lockdown conditions (Castellà & Muro, 2022). The present findings suggest that problematic behavior, sleep dysregulation, and somatic symptoms may be different expressions of broader dispositional and regulatory profiles. Person-centered analysis may consequently offer greater explanatory value than models examining each symptom or behavior separately.

The profile solution was further supported by evidence from high-stress health contexts. Medical personnel exposed to the second wave of the COVID-19 pandemic experienced interconnected symptoms of depression, anxiety, acute stress, and insomnia (Zhao et al., 2021). Such symptom clustering resembles the pattern observed in the sleep-disturbed negative-affect and multidimensional high-susceptibility profiles. The co-occurrence of emotional distress, sleep disturbance, and physical symptoms may therefore reflect a generalized stress-response configuration that emerges across different environmental conditions. The present results extend this literature by demonstrating that similar configurations can be identified within a general adult population rather than only among occupational or clinical groups. This supports the use of unsupervised machine learning as a method for identifying naturally occurring heterogeneity in psychosomatic vulnerability.

Overall, the findings indicate that psychosomatic susceptibility is best conceptualized as a multidimensional configuration. Negative emotionality and sleep disturbance formed a prominent pathway to somatic burden, whereas alexithymia defined a separate emotionally constrained pattern. Coping flexibility appeared to distinguish adaptive from maladaptive configurations, and conscientiousness was the personality trait most strongly differentiated across profiles after negative emotionality. The results therefore support a person-centered model in which individuals with similar somatic symptom scores may differ substantially in emotional awareness, personality, coping, and sleep. Such heterogeneity has important implications because interventions based only on symptom severity may fail to address the mechanisms most relevant to each individual.

Several limitations should be considered when interpreting these findings. The cross-sectional design precluded conclusions regarding causal direction, temporal development, or transitions between profiles. All principal variables were measured through self-report questionnaires, which may have introduced recall bias, response-style effects, shared-method variance, and underreporting or overreporting of psychological and physical symptoms. Although the sample included adults from different regions and demographic groups in Ireland, online recruitment may have favored individuals with greater digital access, research interest, or educational attainment. The identified profiles were data-driven and may therefore depend partly on the selected measures, scaling procedures, clustering algorithms, and range of candidate solutions. Somatic symptom severity was assessed dimensionally and was not verified through clinical examination, while chronic medical and mental health conditions were self-reported. The study also did not assess potentially important variables such as trauma history, health anxiety, perceived stress, social support, physical activity, substance use, medication type, socioeconomic adversity, or objective sleep parameters.

Future studies should replicate the four-profile structure in larger clinical and community samples from Ireland and other cultural settings. Longitudinal designs are needed to determine whether the profiles remain stable, whether individuals move between profiles following major life events or treatment, and whether emotionally constrained participants later develop greater sleep or somatic difficulties. Research should incorporate clinician-rated

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symptoms, medical records, actigraphy, physiological indicators, ecological momentary assessment, and digital behavioral data to reduce dependence on self-report measures. Future analyses could compare additional clustering methods and examine whether trauma exposure, health anxiety, autonomic regulation, social support, occupational stress, lifestyle behavior, and healthcare utilization improve profile differentiation. Intervention studies should also test whether profile membership predicts response to psychotherapy, sleep treatment, emotion-focused interventions, stress-management programs, or integrated psychosomatic care.

The findings support the use of multidimensional psychosomatic assessment rather than relying exclusively on the severity of physical symptoms. Practitioners should evaluate personality-related emotional vulnerability, alexithymia, coping adaptability, and sleep disturbance when adults present with recurrent or disproportionate somatic complaints. Individuals in the emotionally constrained profile may benefit from interventions focused on emotional identification, interoceptive differentiation, and communication of feelings. Those in the sleep-disturbed negative-affect profile may require combined sleep treatment, anxiety regulation, and strategies for reducing physiological hyperarousal. Individuals with multidimensional high susceptibility are likely to need coordinated psychological and medical care addressing emotional awareness, coping rigidity, sleep impairment, health behavior, and chronic illness management simultaneously. The resilient profile should not be viewed as requiring no support, but its adaptive characteristics may serve as targets for preventive programs designed to strengthen coping flexibility, emotional literacy, health routines, and social resources in more vulnerable groups.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

References

Akram, U., Stevenson, J. C., Gardani, M., Allen, S., & Johann, A. F. (2023). Personality and Insomnia: A Systematic Review and Narrative Synthesis. *Journal of Sleep Research*, *32*(6). https://doi.org/10.1111/jsr.14031

Berger, K., Schiefner, F., Rudolf, M. P., Awiszus, F., Junne, F., Vogel, M., & Lohmann, C. H. (2024). Long-Term Effects of Doping With Anabolic Steroids During Adolescence on Physical and Mental Health. *Die Orthopädie*, *53*(8), 608-616. https://doi.org/10.1007/s00132-024-04498-3

Bottiroli, S., Renzi, A., Ballante, E., Icco, R. D., Sances, G., Tanzilli, A., Vecchi, T., Tassorelli, C., & Galli, F. (2023). Personality in Chronic Headache: A Systematic Review With Meta-Analysis. *Pain Research and Management*, *2023*, 1-19. https://doi.org/10.1155/2023/6685372

Castellà, J., & Muro, A. (2022). How Time Perspective, Personality, and Morningness Contributed to Psychological Well-Being During the Coronavirus Lockdown. *Quaderns de Psicologia*, *24*(1), e1752. https://doi.org/10.5565/rev/qpsicologia.1752

Chang, R. S., Lee, M., Im, J. J., Choi, K. H., Kim, J., Chey, J., Shin, S.-H., & Ahn, W. Y. (2023). Biopsychosocial Factors of Gaming Disorder: A Systematic Review Employing Screening Tools With Well-Defined Psychometric Properties. *Frontiers in Psychiatry*, *14*. https://doi.org/10.3389/fpsyt.2023.1200230

Chauhan, A., & Kumar, S. (2022). Stress-Personality Relationship During Covid-19 Restrictions: A Review. *International Journal of Management Public Policy and Research*, *1*(4), 57-63. https://doi.org/10.55829/ijmpr.v1i4.99

Chen, J., & Huang, H. (2024). The Influence of Big Five Personality Traits on Depression and Suicidal Behavior. https://doi.org/10.5772/intechopen.1006564

Conway, B. A., Marwin Machay Indio do Brasil do, C., Helder Sergio Lira Soares, F., Toscanini, A. C., Hasan, R., Mansur-Alves, M., & Rafihi-Ferreira, R. E. (2025). Personality Traits and Insomnia: Direct and Anxiety-mediated Associations. *Journal of Sleep Research*, *34*(6). https://doi.org/10.1111/jsr.70003

Ecker, A., Jarvers, I., Kandsperger, S., Brunner, R., & Schleicher, D. (2025). Temperament and Personality: Preliminary Evidence of Possible Relationships With Multifactorial Stress

JPPR
E-ISSN: 3041-8542

Reactivity in Healthy Adolescents. *Frontiers in psychology*, *16*. https://doi.org/10.3389/fpsyg.2025.1613000

Elagouz, M., Nabih, M. H., ElKaffas, M. E., Hafiz, M., & Ibrahim, I. (2025). Resilience and Its Relation to Alexithymia and Personality Traits in Egyptian Medical Students: A Cross-Sectional Study. https://doi.org/10.21203/rs.3.rs-5510628/v1

Esther, B., & Obosi, A. C. (2023). Influence of Occupational Stress, Personality and Job Demand on Mental Health of Police Officers in Nigeria. https://doi.org/10.21203/rs.3.rs-3263840/v1

Fabbri, M., Beracci, A., & Martoni, M. (2022). Insomnia, Time Perspective, and Personality Traits: A Cross-Sectional Study in a Non-Clinical Population. *International journal of environmental research and public health*, *19*(17), 11018. https://doi.org/10.3390/ijerph191711018

Fukuti, P., Santi, T. D., Nascimento, A. G., Oliveira, L. C. d., Garcia, L. A. Z., Konieczniak, E. M. M., Cabrelon, V., Carrijo, L. D. F., Oliveira, M. C. d., Brañas, M. J., Croci, M. S., Aguiar-Borges, S., Santos, J. M., Sousa, N., Humes, E. C., Menezes, P. R., Miguel, E. C., & Caye, A. (2026). Big Five Personality Traits and Lifestyle: A Cross-Sectional Study in Brazilian Undergraduate Students. https://doi.org/10.21203/rs.3.rs-9622599/v1

Gaggero, G., Dellantonio, S., Pastore, L., Leng, K. S. H., & Esposito, G. (2022). Shared and Unique Interoceptive Deficits in High Alexithymia and Neuroticism. *PLoS One*, *17*(8), e0273922. https://doi.org/10.1371/journal.pone.0273922

Ho, C. S. H., Chua, J. J. E., & Tay, G. W. N. (2022). The Diagnostic and Predictive Potential of Personality Traits and Coping Styles in Major Depressive Disorder. *BMC psychiatry*, *22*(1). https://doi.org/10.1186/s12888-022-03942-y

Holzinger, B., Mayer, L., & Klösch, G. (2021). Personality Traits and Insomnia Symptoms in Shift Workers. *Frontiers in psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.689741

Kulshreshtha, P. (2023). Personality Construct as a Biomarker in Fibromyalgia: A Narrative Review From an Autonomic Rehabilitation Perspective. *Journal of Back and Musculoskeletal Rehabilitation*, *36*(6), 1251-1260. https://doi.org/10.3233/bmr-220353

Listopad, I. W., Michaelsen, M. M., Werdecker, L., & Esch, T. (2021). Bio-Psycho-Socio-Spirito-Cultural Factors of Burnout: A Systematic Narrative Review of the Literature. *Frontiers in psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.722862

Lu, C., Yin, S., Tian, T., Zhao, Z., Wang, L., Zhang, X., Zeng, M., Liu, T., & Wang, L. (2024). Gender-Specific Associations Between Personality Traits and Mental Health Status of Intensive Care Unit Patients' Family Members. https://doi.org/10.21203/rs.3.rs-4454661/v1

Luo, W., & Zhong, B. L. (2025). The Relationship Between Childhood Abuse, Personality, and Depression: A Narrative Review. *Alpha Psychiatry*, *26*(4). https://doi.org/10.31083/ap45405

Min, W., Zhou, B., Li, Z., Tang, N., Zhang, X., Wang, J., Chen, Y., Zhou, Y., Ru-Han, A., Tang, L., Li, G., & Sun, X. (2022). Re-Interpretation of the Mechanism of Type 2 Diabetes Mellitus Based on a Framework of Psychosomatic Medicine: A Real-World Study. *BMC psychiatry*, *22*(1). https://doi.org/10.1186/s12888-022-04315-1

Orrù, G., Piarulli, A., Conversano, C., Grenno, G., & Gemignani, A. (2025). The Interplay of Personality Traits and Psychological Well-Being: Insights From a Study of Italian Undergraduates. *International journal of environmental research and public health*, *22*(2), 132. https://doi.org/10.3390/ijerph22020132

Orzeszek, S., Martynowicz, H., Smardz, J., Wojakowska, A., Bombała, W., Jenča, A., & Więckiewicz, M. (2025). Relationship Between Pain, Quality of Sleep, Sleep Bruxism and Patients' Personality Among Individuals With Reported Orofacial Pain. *Scientific reports*, *15*(1). https://doi.org/10.1038/s41598-025-09978-w

Osimo, S. A., Aiello, M., Gentili, C., Ionta, S., & Cecchetto, C. (2021). The Influence of Personality, Resilience, and Alexithymia on Mental Health During COVID-19 Pandemic. *Frontiers in psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.630751

Parent-Lamarche, A., Marchand, A., & Saade, S. (2021). A Multilevel Analysis of the Role Personality Play Between Work Organization Conditions and Psychological Distress. *BMC psychology*, *9*(1). https://doi.org/10.1186/s40359-021-00703-6

Pilafas, G., & Lyrakos, G. (2021). Psychosomatic Health and Sympathetic Nervous Adaptation of Health Professionals and the General Population During the Second Covid-19 Wave in Greece. Between-Group Comparisons and Regression Analysis. *Health & Research Journal*, *7*(4), 160. https://doi.org/10.12681/healthresj.28160

Rahimi, M. K. A., Zarimeidani, F., Bahreini, H. S., Rahmati, R., & Shahraki, H. R. (2025). Personality Traits and Alexithymia: A Closer Look at University Students in a Cross-Sectional Study. *Medicine*, *104*(10), e41765. https://doi.org/10.1097/md.0000000000041765

Ranjbari, H. T. (2021). Role of Learning Positive Personality Traits in the Promotion of Generational Resilience and Health. *Journal of Rescue and Relief*, 141-148. https://doi.org/10.32592/jorar.2021.13.2.6

Sołtys, A., & Wnuk, M. (2025). Types of Caregivers for People With Alzheimer's Disease in the Context of Their Value System and Personality Traits. *Journal of Alzheimer's Disease*, *109*(3), 1331-1345. https://doi.org/10.1177/13872877251406616

Tu, T. T. H., Watanabe, M., Suga, T., Hong, C., Takao, C., Takenoshita, M., Motomura, H., & Toyofuku, A. (2021). Personality Traits in Burning Mouth Syndrome Patients With and Without a History of Depression. *Frontiers in Psychiatry*, *12*. https://doi.org/10.3389/fpsyt.2021.659245

Wickord, L.-C., & Quaiser-Pohl, C. (2022). Psychopathological Symptoms and Personality Traits as Predictors of Problematic Smartphone Use in Different Age Groups. *Behavioral Sciences*, *12*(2), 20. https://doi.org/10.3390/bs12020020

Williams, P., & Carlson, S. E. (2025). Personality and Emotional Adjustment in Health Risk and Resilience. 431-463. https://doi.org/10.1037/0000394-020

Zhao, Y., Guo, J., Liu, S., Aizezi, M., Zeng, Q., Sidike, A., Abliz, R., Kudireti, A., Xie, Y., Taineikuli, A., & Zhang, B. (2021). Prevalence and Related Factors of Depression, Anxiety, Acute Stress, and Insomnia Symptoms Among Medical Staffs Experiencing the Second Wave of COVID-19 Pandemic in Xinjiang, China. *Frontiers in Public Health*, *9*. https://doi.org/10.3389/fpubh.2021.671400

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