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Non-linear associations between academic burnout and psychological distress and context-dependent effect modification by resilience among medical students: a multicentre cross-sectional study

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Abstract

Medical education combines intensive academic demands, emotionally challenging clinical contexts and prolonged professional socialisation. However, the extent to which different dimensions of academic burnout show heterogeneous associations with psychological distress, and whether these associations modify the role of resilience, remains unclear. We conducted a multicentre cross-sectional online survey of 3,414 medical students. Academic burnout, psychological distress and resilience were assessed using the Maslach Burnout Inventory–Student Survey, Depression Anxiety Stress Scales-21 and Connor–Davidson Resilience Scale-25, respectively. Associations were examined using HC3-robust multivariable regression, restricted cubic splines, quantile regression and flexible non-linear effect-modification models. Academic cynicism had the largest standardised coefficient in the depression model (β = 0.445, FDR-adjusted $q < 0.001$), whereas emotional exhaustion had the largest coefficient in the stress model (β = 0.270, $q < 0.001$). Resilience was negatively associated with all three distress outcomes (β= −0.111 to − 0.071; all $q < 0.001$). Emotional exhaustion and academic cynicism showed non-linear associations with psychological distress (all *P*_nonlinear < 0.001), with steeper associations at higher burnout levels; quantile regression further showed stronger associations at higher conditional quantiles of distress (τ = 0.90 vs τ = 0.50; all $q < 0.001$). The academic cynicism × resilience interaction was consistently significant across depression, anxiety and stress (all q ≤ 0.002), with the inverse association attenuating as academic cynicism increased. Core burnout-related associations and the academic cynicism × resilience interaction pattern were robust across sensitivity analyses, while 10-fold cross-validation showed only modest improvements in out-of-sample RMSE for the flexible models over linear models (1.3%–3.0%). These findings indicate dimension-specific, non-linear and context-dependent associations between academic burnout and psychological distress. Dimension-specific assessment may therefore provide information beyond overall burnout scores in medical education.

1 Introduction

Medical students face sustained academic demands alongside clinical exposure, emotional challenges and professional socialisation. Depression, anxiety, stress and burnout are common in this population, although their prevalence varies substantially across studies and educational contexts (Frajerman et al. 2019; Di Vincenzo et al. 2024). Medical training additionally involves exposure to illness, suffering and ethical conflict while professional identity is being formed, such that burnout may involve both exhaustion and psychological disengagement from learning (Di Vincenzo et al. 2024; Goh et al. 2026). Understanding burnout in medical education therefore requires attention to its specific dimensions rather than reliance on a single overall score.

Academic burnout extends the burnout construct to educational settings and is commonly operationalised using the Maslach Burnout Inventory–Student Survey (MBI-SS), which distinguishes emotional exhaustion, cynicism and academic efficacy (Schaufeli et al. 2002; Hu and Schaufeli, 2009).This educational construct should be distinguished from burn-out as defined in ICD-11, which is restricted to the occupational context(World Health Organization, 2019). This conceptual distinction is

particularly important because, although burnout is consistently correlated with depression and anxiety, the boundaries of these constructs have long been debated; systematic reviews and meta-analyses show that they are closely related but cannot simply be regarded as the same phenomenon (Koutsimani et al. 2019; Bianchi et al. 2015).Among medical students, existing studies have likewise found academic burnout to be associated with depression, resilience and life satisfaction (Cheng et al. 2020; Wang et al. 2022). However, treating burnout as a single total score or reporting only overall correlations may obscure differences between specific dimensions and different forms of psychological distress. The question is therefore not only how high the level of burnout is, but also whether exhaustion, disengagement and efficacy exhibit distinct patterns of psychological association.

Most existing evidence is based on mean associations that assume a constant relationship across the exposure range. Such assumptions may obscure non-linear patterns or stronger associations among students at the upper end of the psychological distress distribution. Conservation of resources theory and the job demands–resources model suggest that sustained demands and resource depletion may generate non-proportional changes in adaptation (Hobfoll 1989; Demerouti et al. 2001; Alarcon et al. 2011). Resilience may also operate differently across burnout contexts. Although higher resilience has been associated with lower burnout and better well-being among medical students, its role may depend on educational and relational conditions (Wang et al. 2022; Goh et al. 2026). Flexible modelling of continuous exposures therefore provides a means of examining both non-linearity and context-dependent effect modification without arbitrary categorisation (Marlin et al. 2023).

We examined three hypotheses: (1) associations with depression, anxiety and stress differ across academic burnout dimensions; (2) associations of emotional exhaustion and academic cynicism with psychological distress are non-linear and stronger at higher conditional quantiles of distress; and (3) the inverse association between resilience and psychological distress varies across burnout levels. Together, these analyses were designed to characterise heterogeneity in burnout–distress associations and the contextual limits of individual psychological resources in medical education.

2 Methods

2.1 Study design, participants and data processing

This was an online cross-sectional survey conducted between October 2025 and February 2026 across 11 medical colleges and universities in China. The reporting followed the STROBE and CHERRIES guidelines (von Elm et al. 2007; Eysenbach, 2004). Members of the society distributed the questionnaire link through the Wenjuanxing platform to medical students at their respective institutions. No incentives were offered for participation. Because accurate numbers of students who actually accessed the questionnaire at each institution were unavailable, response rates were not calculated. The platform allowed only one submission per mobile device. A total of 3,657 records were obtained. After excluding 204 records from participants who did not provide consent, 3,453 entered data cleaning. After further checks for potential duplicate participation, the first valid record from each participant was retained for

the main analysis, resulting in a final inclusion of 3,414 medical students. There were no missing data for the core study variables; therefore, no missing data imputation was performed. Data quality control considered both completion time and mechanical consistency in responding. Completion time below 50% of the sample median (< 146 s) was defined as a fast-response flag; questionnaires were not excluded solely on the basis of a single indicator (Ward and Meade, 2023). The full data cleaning procedure is presented in Supplementary Table S1.

2.2 Study variables and measures

Demographic variables included sex, age, year of study and institution. The main models adjusted for sex, year of study and institution fixed effects, with female, first-year students and "other medical college" as the reference categories. Academic burnout was assessed using the 15-item MBI-SS (Q16–Q30), comprising emotional exhaustion, academic cynicism and academic efficacy (Hu and Schaufeli 2009). Each dimension was scored separately in this study, and no composite total score was calculated. Higher academic efficacy scores indicate greater perceived efficacy and therefore run in the opposite direction to emotional exhaustion and academic cynicism. Cronbach's α for the three dimensions was 0.931, 0.945 and 0.907, respectively, and McDonald's ω was 0.932, 0.944 and 0.908, respectively. Depression, anxiety and stress were assessed using the DASS-21 (Q31–Q51), with seven items per dimension (Lovibond and Lovibond, 1995; Antony et al. 1998). The three-factor structure of the Chinese version of the DASS-21 has been supported (Wang et al. 2016). Cronbach's α values for the three dimensions were 0.935, 0.922 and 0.944, with corresponding McDonald's ω values of 0.937, 0.929 and 0.946. Subscale scores were summed without multiplication by two, yielding a range of 0–21 for each domain. Resilience was assessed using the CD-RISC-25 (Q52–Q76); the original study reported a Cronbach's α of 0.89 (Connor and Davidson, 2003). The Chinese version of the CD-RISC supports a three-factor structure comprising tenacity, strength and optimism, with a total scale reliability coefficient of 0.91 (Yu and Zhang, 2007). The total score was used to represent resilience; Cronbach's α and McDonald's ω were 0.975 and 0.976, respectively. Given that the coefficients exceeded 0.95, interpretation of the results also took into account the number of items and consistent response patterns; high internal consistency was not directly equated with unidimensionality or construct validity.

2.3 Statistical analysis

Depression, anxiety and stress were modelled separately. Continuous predictors were z-standardised, and coefficients from the primary linear models represent the change in outcome SD per 1-SD increase in the predictor. HC3 heteroscedasticity-robust covariance estimators were used for standard errors, 95% CIs and two-sided P values (MacKinnon and White 1985; Long and Ervin 2000). Scale internal consistency was evaluated using Cronbach's α and McDonald's ω, avoiding reliance on α alone (Dunn et al. 2014); construct distinctiveness was assessed using the heterotrait–monotrait ratio (HTMT) (Henseler et al. 2015). Reliability and validity, discriminant validity, and correlational structure are presented in Supplementary Tables S2A–S3.

2.3.1 Multivariable linear regression

With depression, anxiety and stress as dependent variables in separate models, emotional exhaustion, academic cynicism, academic efficacy and resilience were simultaneously included as core predictors, with adjustment for sex, year of study and institution fixed effects. Ordinary least squares regression was used. Standardised β, HC3 robust 95% confidence intervals, P values and R^2 were reported, and multicollinearity was assessed using the variance inflation factor (VIF). Supplementary analyses further evaluated variable contributions and model stability, including VIF and the incremental explanatory power (incremental R^2) after sequentially entering predictors. The results of the relevant supplementary analyses are presented in Supplementary Table S4.

2.3.2 Non-linear associations and distributional heterogeneity

Restricted cubic splines (RCS) were used to evaluate non-linear associations between continuous academic burnout and psychological distress (Desquilbet and Mariotti, 2010). In the main analysis, 4-knot RCS (P5/P35/P65/P95) were fitted separately for emotional exhaustion and academic cynicism, generating 3 spline basis functions. The main model adjusted for resilience, sex, year of study and institution fixed effects; on this basis, models that additionally adjusted for the other two burnout dimensions were used as robustness analyses. HC3 robust joint Wald tests were used to evaluate the overall association, and the non-linear basis functions were tested separately; R^2 was compared between the RCS and the corresponding linear model. Because the three outcomes were markedly right-skewed and had a high proportion of zero scores, quantile regression was further used to estimate associations at the conditional quantiles $\tau = 0.50$, 0.75 and 0.90 (Koenker and Bassett, 1978), in order to examine whether association strength varied across conditional quantiles of psychological distress. The four continuous predictors were standardised using the main sample mean and sample standard deviation (ddof = 1), while outcomes retained their raw total scores on the 0–21 scale. Point estimates were obtained using statsmodels QuantReg, with a convergence tolerance of 1×10^{-6} and a maximum of 10,000 iterations. For primary inference, within-school stratified individual pairs bootstrap was used (B = 2,000) (Hahn, 1995), and 95% confidence intervals were constructed from the Bootstrap distribution percentiles P2.5 and P97.5. For emotional exhaustion and academic cynicism, a 2-degree-of-freedom Bootstrap-Wald test was used to jointly evaluate the overall heterogeneity of β(0.75) and β(0.90) relative to β(0.50), and β(0.90) − β(0.50) was specified as the primary high-quantile contrast; BH-FDR correction was applied separately to the 6 tests in each of the two groups.

2.3.3 Effect modification analysis

Effect modification by resilience was examined in three stages. Effect modification in cross-sectional data is not equivalent to causal interaction or causal buffering (VanderWeele, 2009; Knol and VanderWeele, 2012). First, a traditional linear interaction model was established, in which the focal burnout dimension and resilience were converted to Z scores and a product term was constructed; the model adjusted for the other two burnout dimensions and covariates, modelled the standardised outcome, and used HC3 inference. Second, squared terms for the focal burnout dimension and resilience were added to the same model, and the product interaction was then evaluated to test its

sensitivity to non-linear main effects. The core analysis used a flexible non-linear effect modification model (Marlin et al. 2023). Four-knot RCS main effects were specified for both the focal burnout dimension and resilience, and the three RCS basis functions for the focal burnout dimension were then each multiplied by linear standardised resilience to form three interaction parameters; the model simultaneously adjusted for the other two burnout dimensions and demographic covariates. A 3-degree-of-freedom HC3 robust joint Wald test was used to evaluate the overall interaction, and adjusted average marginal predicted curves with 95% confidence intervals were plotted at resilience P25, P50 and P75. The sensitivity analysis results for the traditional linear interaction and quadratic interaction models are presented in Supplementary Table S5.

2.3.4 Robustness analyses and multiple comparison control

Sample sensitivity analyses included a strict quality control sample (N = 3,339), an adult sample (N = 3,364), retention of the first record for duplicate identities (N = 3,414), and complete exclusion of any duplicate identity (N = 3,376). Covariate sensitivity analyses additionally adjusted for survey period and replaced year of study with age. Centre structure analyses used school cluster-robust covariance, random intercept models and leave-one-centre-out analyses in which each major centre was removed in turn; given the small number of clusters, these served only as sensitivity evidence (Marlin et al. 2023; Cameron and Miller, 2015). Functional form analyses used 3- to 5-knot RCS, respectively; resilience was parameterised as tertiles or quartiles. Construct analyses repeated the full set of analyses with alternative outcomes and alternative exposures.

10-fold cross-validation (random_state = 2025) was used to evaluate the out-of-sample predictive gain of complex models, without replacing association estimation and statistical inference (Arlot and Celisse, 2010) .For emotional exhaustion and academic cynicism separately, linear, RCS and RCS + Interaction models were compared: the linear model was consistent with the adjustment set of the main analysis; the RCS model modelled the focal burnout dimension and resilience with 4-knot RCS, respectively, while retaining the other two burnout dimensions and demographic covariates; and the RCS + Interaction model further added interaction terms between the RCS basis functions of the focal burnout dimension and linear standardised resilience. Randomly shuffled 10-fold splits were used, with 9 folds for training and 1 fold for validation each time; standardisation parameters for continuous variables and RCS knots were estimated only from the training folds and applied to the validation fold. All validation observations were pooled to calculate the root mean square error (RMSE), and the percentage improvement in RMSE relative to the linear model was calculated (Supplementary Table S6). The Benjamini–Hochberg method was used to control the false discovery rate (FDR) (Benjamini and Hochberg, 1995). In the main linear regressions, the 12 regression coefficients generated by the four continuous predictors across the three psychological distress outcomes were defined as one family of tests and were FDR-corrected. Traditional linear interaction, interaction after adding quadratic main effects, and flexible non-linear overall interaction each constituted separate families of tests; the 6 overall cross-quantile heterogeneity tests and the 6 primary contrasts between $\tau = 0.90$ and $\tau = 0.50$ in quantile regression constituted two

separate families of tests. All analyses reported both raw P values and FDR-corrected q values, and interpretation was integrated with effect direction, effect size, 95% confidence intervals, functional form and sensitivity analysis results.

3 Results

3.1 Sample characteristics and distributions of main variables

The final analysis included 3,414 medical students, 70.3% of whom were female. Depression, anxiety and stress scores were right-skewed, with zero-score proportions of 36.8%, 39.4% and 43.1%, respectively (Table 1; Supplementary Table S2A). Internal consistency was high across all scales and dimensions (Cronbach's α and McDonald's ω > 0.90). Pearson and Spearman correlations showed similar patterns: emotional exhaustion and academic cynicism were positively correlated with all three distress outcomes, whereas academic efficacy and resilience were negatively correlated. Correlations were particularly strong between emotional exhaustion and academic cynicism and among depression, anxiety and stress (Supplementary Tables S2A–S3;S7).

Table 1
Basic characteristics of medical students and main study variables (N = 3,414)

Characteristic/measure	n (%)	Mean ± SD	Median (IQR)
Male	1014 (29.7%)		
Female	2400 (70.3%)		
First year	1534 (44.9%)		
Second year	885 (25.9%)		
Third year	631 (18.5%)		
Fourth year	270 (7.9%)		
Fifth year or postgraduate	94 (2.8%)		
17 years	50 (1.5%)		
18 years	1052 (30.8%)		
19 years	1034 (30.3%)		
20 years	719 (21.1%)		
21 years	356 (10.4%)		
22 years	124 (3.6%)		
23 years	60 (1.8%)		
≥ 24 years	19 (0.6%)		
Emotional exhaustion		2.49 ± 1.46	2.60 (1.60–3.40)
Academic cynicism		2.07 ± 1.47	2.00 (1.00–3.00)
Academic efficacy		3.89 ± 1.18	3.83 (3.17–4.67)
Depression		3.70 ± 4.30	2.00 (0.00–7.00)
Anxiety		3.04 ± 4.04	1.00 (0.00–5.00)
Stress		3.55 ± 4.63	1.00 (0.00–7.00)
Resilience		61.77 ± 19.79	60.00 (50.00–74.00)

Note: Percentages use the main analysis sample (n = 3,414) as the denominator; continuous variables are reported as mean ± standard deviation and median (IQR); all main variables were recalculated from the Q16–Q76 scores.

3.2 Multivariable association analysis

After emotional exhaustion, academic cynicism, academic efficacy and resilience were simultaneously included and sex, year of study and institution fixed effects were adjusted for, emotional exhaustion and

academic cynicism were both positively associated with depression, anxiety and stress, although their standardised coefficients showed different numerical patterns across outcome models. The standardised β for academic cynicism in the depression, anxiety and stress models was 0.445, 0.310 and 0.251, respectively, with the largest coefficient in the depression model; the corresponding values for emotional exhaustion were 0.149, 0.202 and 0.270, with the largest coefficient in the stress model. Resilience showed negative associations in all three models, with standardised β of − 0.111, − 0.071 and − 0.097, respectively. By contrast, the standardised β for academic efficacy was − 0.024, − 0.005 and − 0.004, respectively, all close to zero, and all 95% confidence intervals crossed zero. The explanatory power of the models was R^2 = 0.431 for depression, R^2 = 0.302 for anxiety and R^2 = 0.329 for stress. After Benjamini–Hochberg correction, the main associations of emotional exhaustion, academic cynicism and resilience remained statistically supported (Table 2; Supplementary Table S4).

Table 2
Multivariable associations of academic burnout dimensions and resilience with depression, anxiety and stress

Outcome	Predictor	Standardised β	Lower 95% CI	Upper 95% CI	*P* value	FDR-adjusted *q* value	Model R^2
Depression	Emotional exhaustion	0.149	0.096	0.202	< 0.001	< 0.001	0.431
	Academic cynicism	0.445	0.383	0.506	< 0.001	< 0.001	0.431
	Academic efficacy	−0.024	−0.055	0.007	0.133	0.145	0.431
	Resilience	−0.111	−0.152	−0.070	< 0.001	< 0.001	0.431
Anxiety	Emotional exhaustion	0.202	0.147	0.257	< 0.001	< 0.001	0.302
	Academic cynicism	0.31	0.242	0.378	< 0.001	< 0.001	0.302
	Academic efficacy	−0.005	−0.042	0.032	0.78	0.78	0.302
	Resilience	−0.071	−0.119	−0.023	0.004	0.006	0.302
Stress	Emotional exhaustion	0.27	0.212	0.328	< 0.001	< 0.001	0.329
	Academic cynicism	0.251	0.185	0.318	< 0.001	< 0.001	0.329
	Academic efficacy	−0.004	−0.038	0.031	0.841	0.841	0.329
	Resilience	−0.097	−0.140	−0.053	< 0.001	< 0.001	0.329

Note: Outcomes and continuous predictors were z-standardised. Models included emotional exhaustion, academic cynicism, academic efficacy and resilience, adjusting for sex, year of study and institution fixed effects. OLS regression with HC3-robust standard errors provided 95% CIs and P values. The 12 coefficients across four predictors and three outcomes constituted one family for Benjamini–Hochberg FDR correction. Differences in standardised coefficient magnitude were descriptive; no formal coefficient comparisons were performed.

3.3 Non-linear association analysis

Emotional exhaustion and academic cynicism showed significant overall and non-linear associations with all three psychological distress outcomes (all $P < 0.001$). Across outcomes, associations were relatively shallow at lower exposure levels and became steeper at higher levels. RCS models increased R^2 by approximately 0.013–0.021 relative to the corresponding linear models, indicating modest gains in

explained variance. The supplementary analysis of academic efficacy showed shallow U-shaped associations, with model-based minima at approximately 4.16–4.40; however, these patterns were sensitive to knot specification and were therefore treated as exploratory (Supplementary Fig. S1; Supplementary Table S8). Associations for emotional exhaustion and academic cynicism remained significant after mutual adjustment for the other burnout dimensions (all $P < 0.001$; Fig. 1; Supplementary Table S9).

3.4 Quantile regression analysis

Quantile regression showed stronger associations of emotional exhaustion and academic cynicism with psychological distress at higher conditional quantiles. From $\tau = 0.50$ to $\tau = 0.90$, coefficients for emotional exhaustion increased by 0.730, 1.316 and 1.625 for depression, anxiety and stress, respectively; corresponding increases for academic cynicism were 1.410, 1.359 and 0.957. All six cross-quantile heterogeneity tests and prespecified $\tau = 0.90$ versus $\tau = 0.50$ contrasts remained significant after FDR correction (all $q < 0.001$). In contrast, the inverse association between resilience and psychological distress attenuated at higher conditional quantiles (Fig. 2; Supplementary Table S10).

3.5 Effect modification analysis of resilience

Neither linear nor quadratic interaction models showed stable evidence; the flexible non-linear model identified consistent effect modification by resilience. The academic cynicism × resilience interaction remained significant for depression, anxiety and stress after FDR correction (all $q \leq 0.002$), whereas the emotional exhaustion × resilience interaction was supported only for depression and anxiety and the academic efficacy × resilience interaction showed no consistent pattern (Supplementary Tables S5, S11). At low-to-moderate levels of academic cynicism, higher resilience corresponded to lower predicted psychological distress; this difference narrowed as cynicism increased and the predicted curves converged (Fig. 3).

3.6 Sensitivity analyses and cross-validation

The main association patterns remained broadly stable across different sample definitions, approaches to handling school clustering structure, and specifications of the RCS functional form. The positive associations of emotional exhaustion and academic cynicism with psychological distress were consistent in direction, and the negative association between resilience and psychological distress remained broadly stable. When school cluster-robust inference was used, the association between resilience and anxiety no longer reached statistical significance ($\beta = -0.071$, 95% CI − 0.164–0.023, $P = 0.122$), whereas other core associations remained broadly consistent. Under different RCS knot specifications, the non-linear associations of emotional exhaustion and academic cynicism and the academic cynicism × resilience interaction pattern remained stable (Supplementary Tables S9–S12). Ten-fold cross-validation showed that the out-of-sample predictive improvement of the complex models was limited. The RMSE of the linear model for depression, anxiety and stress was 3.264, 3.398 and 3.816, respectively. When academic cynicism was the focal exposure, the RMSE improvement of the RCS + Interaction model relative to the linear model was 3.031%, 2.359% and 2.084%, respectively; when

emotional exhaustion was the focal exposure, the corresponding improvements were 2.199%, 1.254% and 1.421%. The improvement for the RCS model ranged from 1.006% to 2.257% (Supplementary Table S6).

4 Discussion

This study shows that the associations between academic burnout and psychological distress among medical students are dimension-specific, non-linear and context-dependent. The standardised coefficient for academic cynicism was largest in the depression model, whereas that for emotional exhaustion was largest in the stress model; the associations of both were stronger at higher burnout levels and at higher conditional quantiles of psychological distress. Resilience was associated with lower psychological distress, but this association weakened as academic cynicism increased. Although the complex models improved the characterisation of association shapes, 10-fold cross-validation showed that their out-of-sample RMSE improved by only approximately 1.3%–3.0%, suggesting that their gain was mainly in explanation rather than prediction.

Different burnout dimensions exhibited distinct patterns of association with psychological distress, further supporting the interpretation of academic burnout as a multidimensional construct. The MBI-SS distinguishes emotional exhaustion, cynicism and academic efficacy as related but conceptually distinct dimensions of student burnout (Schaufeli et al. 2002). In this study, the standardised coefficient for academic cynicism was largest in the depression model, whereas that for emotional exhaustion was largest in the stress model. This pattern is consistent with the conceptual characteristics of the two: disengagement bears a degree of phenomenological affinity to the reduced motivation and loss of interest seen in depression, whereas exhaustion more closely reflects fatigue and tension under sustained demands. However, given the known construct overlap between burnout and depression, these results should not be interpreted as mutually independent psychological mechanisms (Koutsimani et al. 2019; Bianchi et al. 2015). The distinct association patterns across burnout dimensions suggest that a single total score may obscure potentially informative differences. By contrast, the independent association of academic efficacy in the linear models was close to zero, and its non-linear results were sensitive to knot specification; it is therefore more appropriately interpreted as a supplementary finding. In the context of medical education, academic cynicism may also involve a weakening of the meaning of learning and professional engagement, which aligns with the emphasis on ongoing socialisation and meaning-making in professional identity formation (Goh et al. 2026; Cruess et al. 2015) .However, because this study did not directly measure professional identity or the meaning of learning, this interpretation requires further verification.

Non-linear and quantile analyses indicated that average linear effects did not fully characterise burnout–distress associations. Emotional exhaustion and academic cynicism showed steeper associations at higher exposure levels and larger coefficients at higher conditional quantiles of psychological distress. This pattern is compatible with conservation of resources and job demands–resources perspectives, which posit non-proportional changes under sustained demands and resource depletion (Hobfoll 1989;

Demerouti et al. 2001; Alarcon et al. 2011). However, the cross-sectional design cannot distinguish resource-loss processes from reverse-direction associations or shared environmental influences. These curves therefore represent statistical non-linearity rather than clinical or educational thresholds. Moreover, the modest 1.3%–3.0% improvement in out-of-sample RMSE indicates that flexible models primarily refined the characterisation of association shape rather than individual prediction (Marlin et al. 2023).

The resilience–distress association varied across levels of academic cynicism. Although higher resilience has previously been associated with lower depression and burnout among medical students (Cheng et al. 2020; Wang et al. 2022), the inverse association in this study weakened as academic cynicism increased. This pattern was consistently identified only after allowing for non-linear main effects and effect modification, indicating that functional-form assumptions may influence the detection of interaction (Marlin et al. 2023). The convergence of predicted distress across resilience levels at high cynicism should not be interpreted as resilience becoming irrelevant; rather, its cross-sectional association with distress was weaker in this context. This finding supports conceptualising resilience within relational and educational contexts rather than solely as an individual attribute (Goh et al. 2026; Carrard et al. 2024).

These findings have direct implications for burnout identification in medical education. Assessments should retain dimension-level information on emotional exhaustion, academic cynicism and academic efficacy, rather than relying solely on overall scores. For students with high exhaustion or high disengagement, identification should further take into account contextual factors such as study load, opportunities for recovery, sense of belonging and professional engagement, in conjunction with their levels of psychological distress. Previous studies have shown that institutional climate, sense of belonging, social support and faculty–student relationships are all associated with burnout among medical students (Yu et al. 2023; Leep Hunderfund et al. 2025), whereas the effects of resilience training on different psychological outcomes are heterogeneous (Sperling et al. 2026). Therefore, individual psychological resources should be understood within specific learning environments, and burnout should not be attributed simply to inadequate individual adaptation. Given that this study did not directly measure the above educational environment factors, their specific roles still require verification through longitudinal and intervention studies.

5 Strengths and limitations

This study combined a large multicentre sample with multidimensional measures of academic burnout and psychological distress and complementary analyses of mean, non-linear and distribution-specific associations. Several limitations should be considered. First, the cross-sectional design precludes inference about temporal or causal direction. Second, web-based self-report measures remain susceptible to measurement error, common method bias and unmeasured confounding. Third, professional identity, specialty, professional commitment and clinical learning experiences were not directly assessed, limiting interpretation of the mechanisms underlying academic cynicism. Finally,

sparse observations at the extremes of the exposure distributions warrant cautious interpretation of spline tails. Longitudinal studies incorporating individual and educational-context measures are needed to examine these associations over time.

6 Conclusions

Academic burnout showed dimension-specific and non-linear associations with psychological distress among medical students. Academic cynicism had the largest standardised coefficient in the depression model, whereas emotional exhaustion had its largest coefficient in the stress model. The inverse association between resilience and psychological distress weakened as academic cynicism increased. These findings support dimension-specific assessment of academic burnout and suggest that individual psychological resources should be interpreted within their educational context. Given the cross-sectional design, the results should not be interpreted causally or used to define clinical or educational thresholds.

Declarations

Competing interests The authors declare no competing interests.

Data availabilityThe de-identified dataset, the English version of the survey questionnaire, and the analysis resources are available as supplementary files accompanying this article. The de-identified dataset is provided for peer review and research purposes only, in accordance with the ethics approval and the informed consent obtained from all participants, which guarantee confidentiality and restrict data use to academic research. Further requests for data access will be handled in accordance with the ethics approval and participant consent.

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Figures

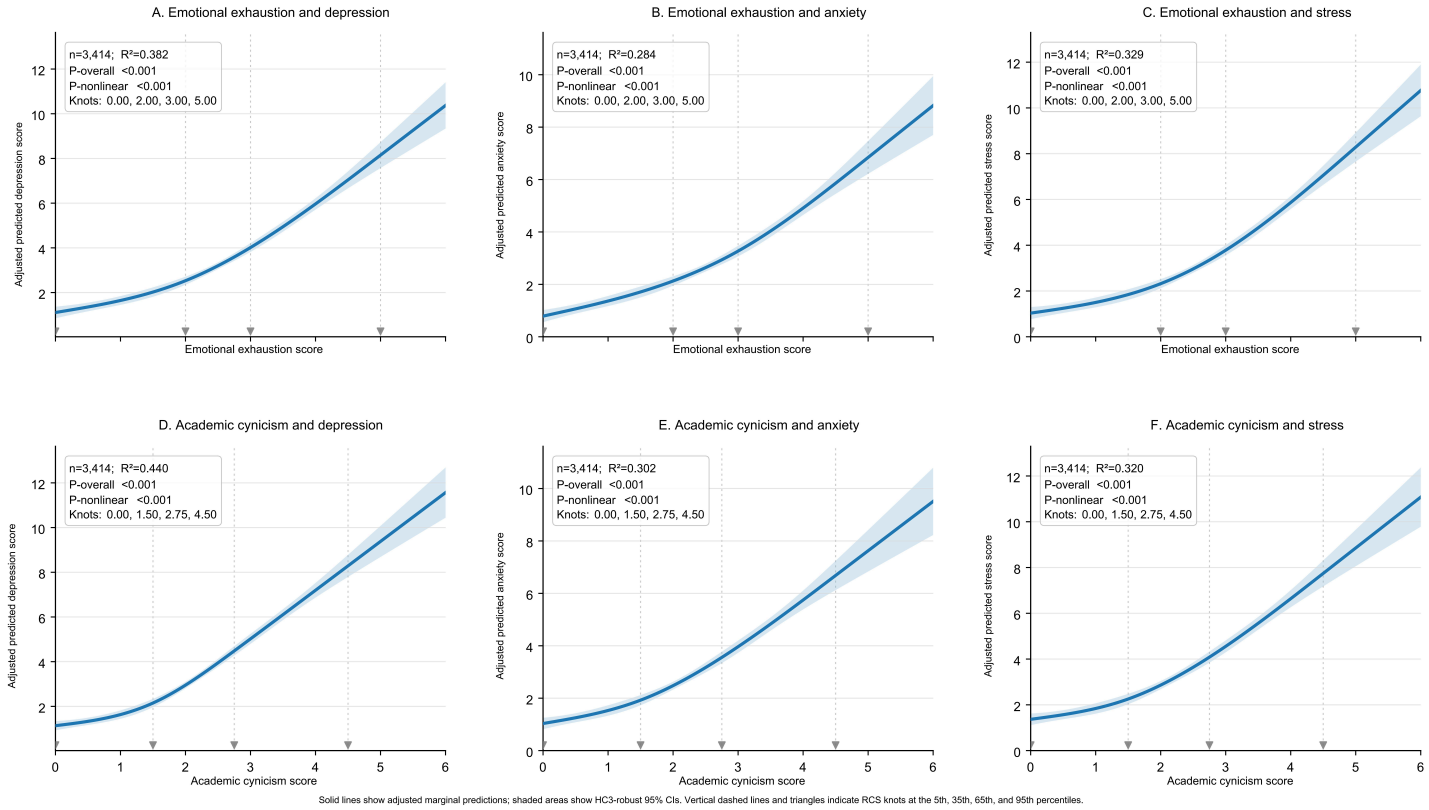


Figure 1

Restricted cubic spline associations of emotional exhaustion and academic cynicism with depression, anxiety and stress

Note: A–C show associations of emotional exhaustion with depression, anxiety and stress, respectively; D–F show corresponding associations for academic cynicism. Solid lines represent adjusted average marginal predicted values and shaded areas HC3-robust 95% CIs. Vertical dashed lines denote RCS knots at the 5th, 35th, 65th and 95th percentiles of the exposure distribution. Models adjusted for resilience, sex, year of study and institution fixed effects. Boxes report N, model R^2, overall and non-linearity P values, and knot locations. RCS, restricted cubic spline; CI, confidence interval.

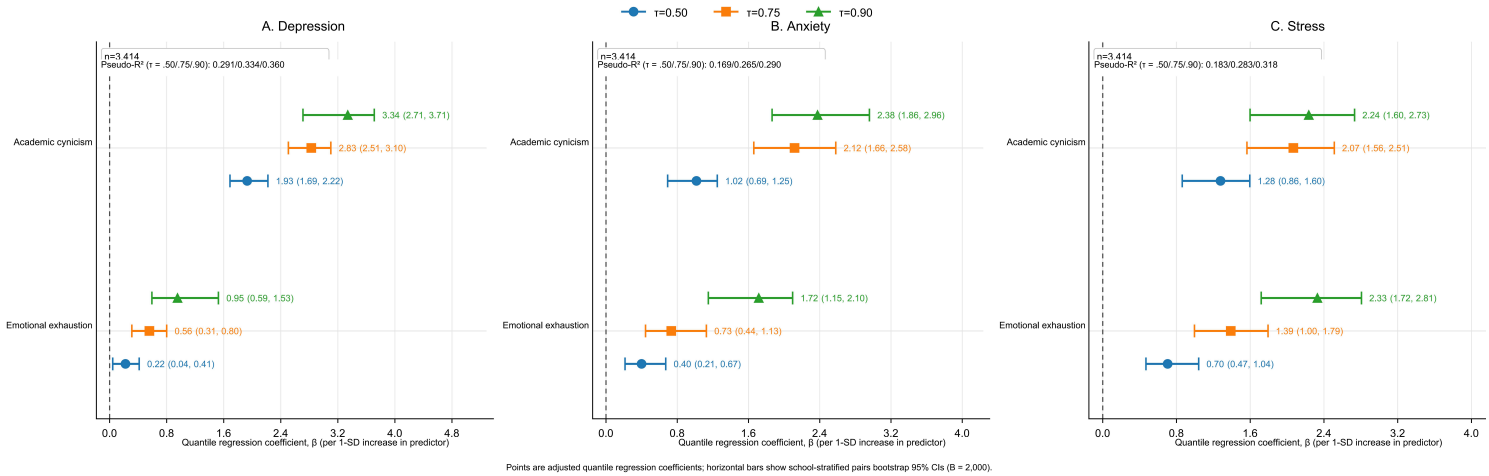


Figure 2

Adjusted quantile regression coefficients for the associations of emotional exhaustion and academic cynicism with psychological distress

Note: A–C show adjusted quantile regression coefficients for depression, anxiety and stress, respectively, at τ = 0.50, 0.75 and 0.90. Horizontal lines indicate within-school stratified pairs-bootstrap 95% CIs (B = 2,000). Coefficients represent the change in the corresponding conditional quantile of the raw outcome score per 1-SD increase in the predictor. Models included emotional exhaustion, academic cynicism, academic efficacy, resilience, sex, year of study and institution fixed effects. Boxes report the sample size and pseudo-R^2 for each quantile model. β, quantile regression coefficient; CI, confidence interval; SD, standard deviation; τ, conditional quantile.

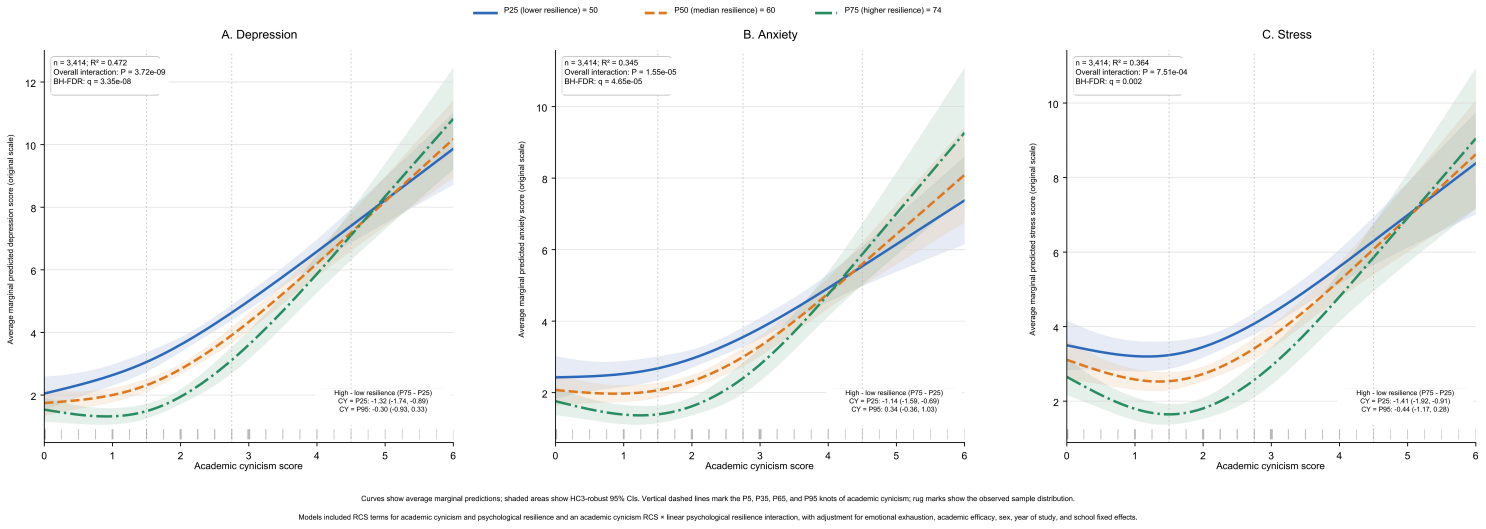


Figure 3

Non-linear effect modification by resilience of the academic cynicism–psychological distress relationship

Note: A–C show adjusted average marginal predicted values for depression, anxiety and stress, respectively, at the 25th (50), 50th (60) and 75th (74) percentiles of resilience. Shaded areas indicate HC3-robust 95% CIs. Vertical dashed lines denote RCS knots at the 5th, 35th, 65th and 95th percentiles of academic cynicism; rug marks show the observed exposure distribution. Models included RCS terms for academic cynicism and resilience, their specified interaction terms, and adjustment for emotional exhaustion, academic efficacy, sex, year of study and institution fixed effects. The upper-left box reports N, R^2, the 3-df overall interaction *P* value and FDR-adjusted q value; the lower-right box reports the predicted difference between the 75th and 25th resilience percentiles at the 25th and 95th percentiles of academic cynicism. RCS, restricted cubic spline; CI, confidence interval; FDR, false discovery rate. Associations are cross-sectional and should not be interpreted as causal buffering effects.

Supplementary Files

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- HSSCFinalSupplementaryTablesS1S111.docx