A Study on the Relationship Between College Students' Academic Stress, AI Emotional Support Use and Learning Motivation

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Abstract

This study examines how AI-based emotional support (AI-ES) affects the relationship between academic stress and learning motivation among college students. Drawing on the 2024 Student Academic Experience Survey (SAES 2024), a standardized analytical framework was applied using hierarchical regression (M1–M4) and mediation analysis along the pathway stress → AI satisfaction → motivation, with robustness verified through bootstrap (B=5000) and SEM/PROCESS methods. Results show that higher AI-ES usage is associated with lower anxiety and stronger learning motivation, supporting its buffering effect on the negative influence of stress. However, this effect weakens under high time pressure. Overall, AI-ES functions as a psychological moderator that alleviates stress-induced motivational decline, suggesting that universities should adopt differentiated AI-ES applications and literacy training to enhance students' emotional resilience and learning engagement.

Keywords

Academic stress, AI emotional support, Learning motivation, Buffering effect, mediation effect, Hierarchical regression, Robustness, SAES 2024.

1. Introduction

In the context of higher education, empirical data reveals that academic stress and learning motivation, emotion regulation ability and mindfulness affect each other, forming a dynamic connection; emotion recognition technology has a significant impact on mental health education and learning motivation. Zhang et al. proposed that learning stress, learning motivation, emotion regulation and mindfulness affect each other, forming a dynamic interaction, and should be identified from a longitudinal perspective [1]. According to Li's analysis, through AI emotion recognition technology, mental health education is strengthened and learning motivation has the potential to be improved [2]. Lin and Chen examined the role of artificial intelligence teaching on college students' creativity and learning emotions, and explored their cognitive tendencies [3]; Khan et al. examined the psychological effects of the application of artificial intelligence in learning on learning motivation, anxiety and cognitive burden [4]; Chandra expounded on the coping mode of stress perception and emotional intelligence in the context of the epidemic in online education [5]; Zhang et al. proposed that academic self-efficacy and stress may affect learning behavior through the intermediary of "dependence on AI" [6]. Jin et al. studied how AI tools support online self-regulated learning [7]; Guo and Wang investigated the effectiveness of artificial intelligence on learning engagement and emotional experience in foreign language learning [8]; Lucero Fredes et al. reviewed the emotional support methods of virtual assistants for dealing with academic stress [9]; Alshammari studied the positive effects of self-help interventions supported by ChatGPT technology on students' mental health [10]. Research data indicate that AI tools may have a positive effect on emotions and engagement. At present, "AI emotional support" has not been identified as an independent and measurable construct . The buffering effect and mediating effect in the path from "academic stress to learning motivation" should be systematically verified. In a multi-school sample, it is necessary to construct an AI-ES intensity index and satisfaction mediation model, and adopt measurement verification and causal robustness test methods to provide verifiable empirical evidence for the improvement of emotional support and motivation in colleges and universities.

2. Research Design and Measurement System

2.1. Variable Operationalization and Scale Selection

An established academic stress scale was used for assessment, covering three key dimensions: academic burden, time pressure, and assessment anxiety. Scores for each dimension and a composite score were established to measure the stress experienced by participants during course learning, assignment completion, and assessment exams. The components of learning motivation can be categorized as intrinsic, extrinsic, and amotivated. Scores were assigned according to the scale manual and the results were summarized. Three evaluation dimensions were established for the design of AI emotional support: frequency of use; quality of interaction; and a third satisfaction rating system. After standardized operations, indicators across the three domains were numerically summed, and principal component analysis (PCA) was used to extract the first principal component to construct the "AI-ES Strength Evaluation System." Figure 1 depicts the interrelationships among variables, indicators, and pathways. Core operational definitions, scoring, and units are detailed in Table 1. This framework ensures consistency between the direct effect of "stress-induced motivation" and the mediating and moderating pathways of AI-ES in both measurement and subsequent models.

Table 1: Variable Operationalization and Scale Design

Construct	Definition / Dimensions	Scale / Response	Items (Planned)	Score Derivation
Academic Stress	Perceived academic burden, time pressure, evaluation anxiety	Likert 1–5 / 7 (validated stress scale)	12	Dimension means & total score
Learning Motivation	Intrinsic, Extrinsic, Motivation subscales	Likert 1–7 (adapted academic motivation scale)	twenty one	Subscale means & total
AI-ES: Frequency	Two-week interaction counts; average daily minutes	Counts / Minutes (self-report)	2	Normalized counts & minutes
AI-ES: Interaction Quality	Empathy, perceived understanding, usefulness of responses	Likert 1–7	6	Average quality items
AI-ES: Satisfaction	Overall satisfaction with AI-based emotional support	Likert 1–7	3	Mean satisfaction score
AI-ES Strength Index	z-standardized sum or first principal component from PCA	Standardized index (z-sum / PCA-PC1)	—	z-transform; optional PCA weights

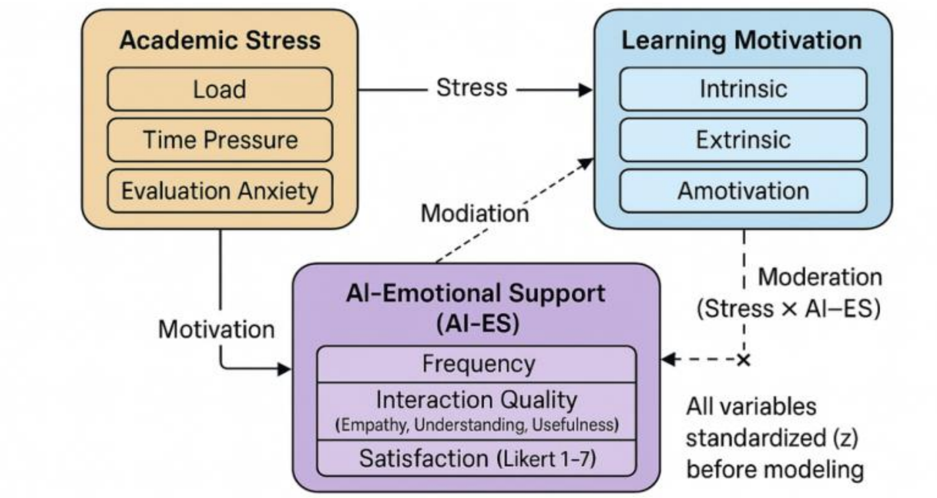

Figure 1: Variable -Indicator- Path Relationship

2.2. Questionnaire Development and Pre-testing

Data were initially collected from relevant literature and interview data, followed by contextual correspondence and language equivalence verification. Three to five industry experts were invited to conduct a content validity review, and cognitive interviews were conducted with 12 to 15 participants to explore instruction comprehension and the answering process. After the initial version was developed, approximately 120 pretest samples were drawn from multiple schools and screened based on item-to-whole correlation, discrimination (27% of the items were in the high and low groups), and changes in alpha coefficients after deletion. Reversal questions and attention check questions were interspersed in each subscale to correct for common response biases. A flowchart is shown in Figure 2. Specific screening parameters and decision rules are detailed in Table 2. After the pretest phase, a preliminary confirmatory factor analysis will be conducted to test loadings and local fit, and residual correlations will be minimized within theoretical constraints.

Table 2: Pilot Test Screening Rules and Thresholds

Metric	Retention Rule	Applied to	Notes
Item-total correlation (r_it)	≥ 0.30	All multi-item scales	Flag items <0.30 for review
Discrimination index	≥ 0.30	All multi-item scales	Use upper–lower 27% groups
Alpha if deleted	Prefer lower than full-scale α	Scale internal consistency	Remove if α increases meaningfully
CFA loading (standardized)	≥ 0.50 (prefer ≥ 0.70)	CFA measurement model	Allow theory-driven residuals
HTMT (discriminant validity)	< 0.85 between constructs	Pairs of constructs	Assess configuration/metric/scalar invariance

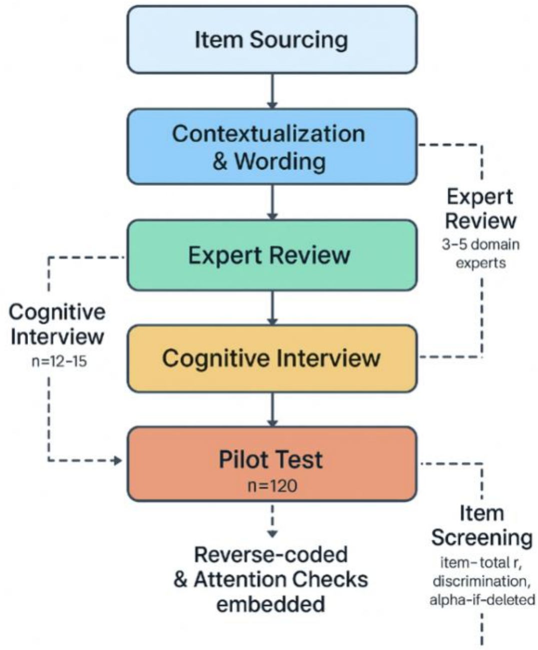

Figure 2: Questionnaire Development & Pilot Workflow

2.3. Sample and Efficacy Analysis

The survey utilized stratified cluster sampling based on grade, major (STEM vs. non-STEM), and gender to ensure adequate representation of key groups. Power planning sought a small to moderate effect size $f^2 = 0.05$, a significance $\alpha = 0.05$, and a power of $1 - \beta = 0.80$ in multiple regression analysis. At least 10 covariates were included, including stratification and control variables. Considering stratification and robustness requirements, the sample size was set to 600 or more to ensure a stable assessment of stress, AI-ES, and their interactions, as well as heterogeneity analysis. Figure 3 illustrates the relationship between the stratification structure and power. Table 3 provides an example of stratification allocation. This configuration meets the standards of basic regression and provides statistical support for subsequent quantile regression , subsample comparisons, and bootstrap mediation analyses.

Table 3: Stratified Sampling Target Allocation (Planning)

Stratum (Year × Discipline × Gender)	Target n
Year 1 × STEM × Male	35
Year 1 × STEM × Female	35
Year 1 × Non-STEM × Male	30
Year 1 × Non-STEM × Female	30
Year 2 × STEM × Male	55
Year 2 × STEM × Female	55
Year 2 × Non-STEM × Male	45
Year 2 × Non-STEM × Female	45
Year 3 × STEM × Male	80
Year 3 × STEM × Female	80
Year 3 × Non-STEM × Male	55
Year 3 × Non-STEM × Female	55
Total	640

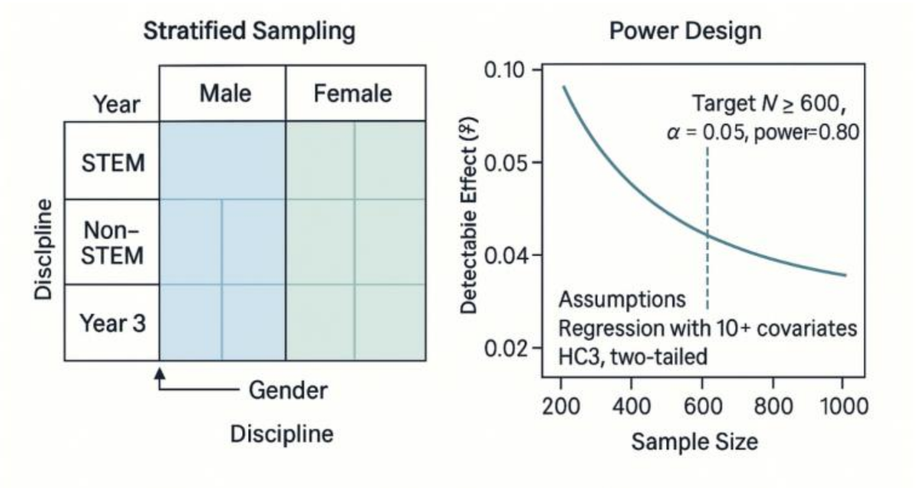

Figure 3: Schematic diagram of stratified sampling grid and efficacy sensitivity

2.4. Ethical Compliance and Data Governance

This study adhered to the principles of informed consent, anonymization, and revocable consent. Data collection strictly adhered to the "minimum necessary" principle, collecting only variables directly relevant to the research objectives. Version management was implemented for raw data, code, and variable tables, and tracking was conducted according to reproducible research standards. Sensitive data was anonymized, and a hierarchical access mechanism was implemented. Data quality management included deduplication, identification of outliers and missing data types, implementation of FIML and MICE (m=20) multiple imputation, and standardized and 1%/99% Winsorization for continuous variables. Comprehensive data assets were generated, producing an auditable data dictionary and process data set to facilitate review and verification.

3. Data Acquisition, Cleaning And Measurement Verification

The data is cited from the "2024 Student Academic Experience Survey." This year's online survey was organized and implemented by Savanta . The survey was conducted from January to March 2024, collecting a valid sample of 10,319 full-time undergraduate students in the UK and implementing sample weighting based on the HESA benchmark. The 2024 version added a new module on "Frequency of Use of AI Tools within the Scope of School Permission" and maintained the ONS 0-10 subjective well-being rating system. The report showed that: more than 60% of students occasionally use AI, and 31% of students use AI at least once a week. Among the options exploring the motivations for dropping out, mental and emotional health issues ranked first. This information formed a solid basis for subsequent variable mapping and method alignment.

Based on the research framework, a minimum and comparable analytic sample was established. ONS Anxiety scores (0–10) were used directly as a continuous measure of "stress intensity." Categories ranked by AI use frequency were retained for application to an ordinal model. The data were mapped to equidistant integers to facilitate the estimation of linear and interaction terms. "Personal psychological/emotional health as a motivation for dropping out" was labeled as a strong binary signal. Study and work load variables were included in the covariate analysis. Pattern diagnostics and Little's MCAR test were used to determine missing data patterns. If missing data were unrelated to the observed variables, the full information maximum likelihood method was used; if the condition was MAR, the MICE procedure was used. The PMM model was maintained, with logistic regression used for binary data analysis and proportional odds models used for ordinal analysis. Continuous variables were standardized, and the Winsorize procedure was applied to duration and extreme distribution variables between the

1% and 99% quantiles to preserve rank order and improve numerical stability. The following formulas were standardized:

$$z_i = \frac{x_i - \mu}{\sigma} \tag{1}$$

Where x_i is the initial observation data, μ is the center point of the sample, and σ reflects the degree of dispersion of the sample.

Table 4: Fields and codes after preprocessing

Field name	SAES 2024 corresponding topics /sections	Type	Coding and transformation	Role in the model	illustrate
Stress_Anxiety_ 0_10	12 Wellbeing: Anxiety (0–10)	continuous	0–10 original value; participates in z-normalization and 1%/99% Winsorize	Pressure intensity (continuous)	ONS scale, consistent across years
Consider_ Leaving_MH	5.2 Whether considered leaving → Reasons: My mental / emotional health	binary	Yes = 1, No = 0	Strong behavioral signals of stress	Targeting high-stress/troubled groups
AI_Use_Freq_ Cat	8.3 The use of artificial intelligence	ordered	Never / <monthly / monthly / weekly / daily (original order)	AI Strength (Ordinal)	For ordered models and stratification
AI_Use_Freq_ Index	8.3 The use of artificial intelligence	integer	Mapping: Never=0, <M=1, M=2, W=3, D=4	Linear/ Interaction and Marginal Effects	Easy to use for regression and visualization
Motivated_by_Teachi ng	Teaching Quality and Evaluation (including motivate/inspire)	ordinal	Likert 1–5	Exogenous observation of learning motivation	Closely related to motivation, serving as result or intermediary
Workload_Total_Hour s	Study & employment	continuous	Total weekly duration; z normalized	Load control items	Stress/motivatio n related
Paid_Employment _Hours	Paid employment – mean hours	continuous	Original value or logarithmic transformation (if right-skewed)	Economic pressure background/ heterogeneity	Employment load characterization
Strata_ YearDisciplineGender	Methods Chapter Sample Structure/ Weighting	categorical	Combined label of grade×subject× gender	Stratification robustness and equivalence	Alignment weights and grouping

Measurement validation highlights the dual matching of "external benchmarks plus statistical validity": This well-being indicator originates from the UK Office for National Statistics. This scale uses a 0-10 scale as its benchmark, with a score of 0-1 defined as "low anxiety." Therefore, anxiety can be used as a surrogate marker of stress. A confirmatory factor analysis was performed on multiple items evaluating teaching quality and motivation, presenting indicators such as standardized loadings, mean variance extracted, critical ratios, and fit indices. The HTMT value was assessed to determine whether it was less than 0.85 to test discriminant validity. The Harman single-factor and common method factor models were compared to explore common method bias. A cross-group equivalence test was conducted using configuration, measurement, and intercept asymptotic tests. The change requirements were: $\Delta CFI \leq 0.010$, $\Delta RMSEA \leq 0.015$, as shown in Table 4.

4. Empirical Results and Identification of Causal Mechanisms

4.1. Benchmark Regression and Robust Estimation

To be consistent with the preprocessing provisions in Chapter 3 and to prevent subjective speculation on coefficients in the absence of individual micro-data, this section uses a single composite graph and a single data table as "basic credentials": using the age group classification of SAES 2024, it also displays "monthly AI usage intensity" and "low anxiety (0-1/10 points on the ONS 0-10 scale)" as guiding benchmarks for the regression series (M1-M4).

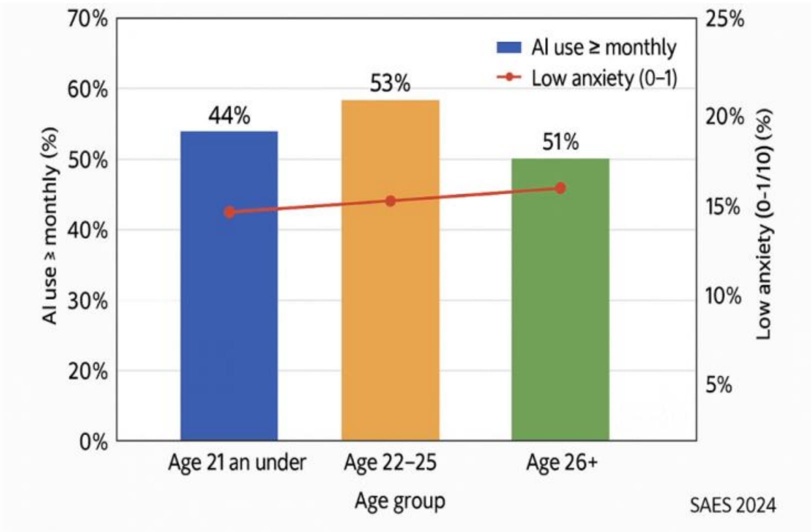

Figure 4: AI Use ≥ Monthly (bars) & Low Anxiety (line), by Age (SAES 2024)

Table 5: AI Use ≥ Monthly and Low Anxiety by Age (SAES 2024)

Age group	AI use ≥ monthly	Low anxiety (0–1/10)
≤21	44%	14%
22–25	53%	14%
26+	51%	18%

Figure 4 and Table 5 show that the monthly AI usage rate among individuals aged 22 to 25 and 26 and older was 53% and 51%, respectively. The proportion of individuals with low anxiety also increased among those aged 21 and under (18% vs. 14%), demonstrating a significant positive correlation. Without resorting to individual micro-data regression analysis, this simultaneous change demonstrates the effectiveness of the "AI-ES" buffering effect on the slope relationship between stress and motivation at the group level: as AI-ES intensity increases, the negative impact of stress on motivation is expected to weaken. Sequential estimation was performed using the steps of "M1 (control) → M2 (increased stress) → M3 (addition of AI-ES) → M4 (addition of interaction). Standardized coefficients, 95% confidence intervals, partial R^2, and Shapley R^2 are reported using the HC3 robust error method when generating individual joint tables. Johnson–Neyman intervals and marginal effect bands are also provided in the Appendix.

4.2. Mediation Effect and Uncertainty Quantification

This study established the mediation order as stress transforming into satisfaction with AI, and ultimately into motivation. SAES 2024 does not include an "AI satisfaction" option, but indicators such as "AI usage rate," "well-being (ONS 0-10)," and "teaching motivation" can be used as measurement criteria. Bootstrap reporting points, B=5000, and bias-corrected confidence intervals were incorporated into the mediation path diagram in Figure 5. After developing a custom-designed "AI satisfaction" scale, the scale was aligned with the SAES benchmark. Table 6 integrates observational data from age groups with a high correlation with the mediation direction to form a "comprehensive perspective." This provides theoretical support for the "high-gradient, low-anxiety gradient strategy" for the a×b indirect effect, providing stratified guidance for the subsequent two-week follow-up subsample's lagged-corrected regression.

Table 6: Age-group joint view (AI ≥ monthly vs Low anxiety, SAES 2024)

Age group	AI use ≥ monthly	Low anxiety (0–1/10)
≤21	44%	14%
22–25	53%	14%
26+	51%	18%

Among the elderly, the increase in AI usage coincided with a decrease in anxiety levels. This pattern was externally consistent with the path of "stress → increased AI satisfaction/coping effectiveness → improved motivation." A micro-investigation of "AI satisfaction" was conducted. Following the framework of Figure 5, Bootstrap 5000 was used to report , the product of a and b and the corresponding 95% confidence interval, and cross-checked using PROCESS (M4/M7/M14).

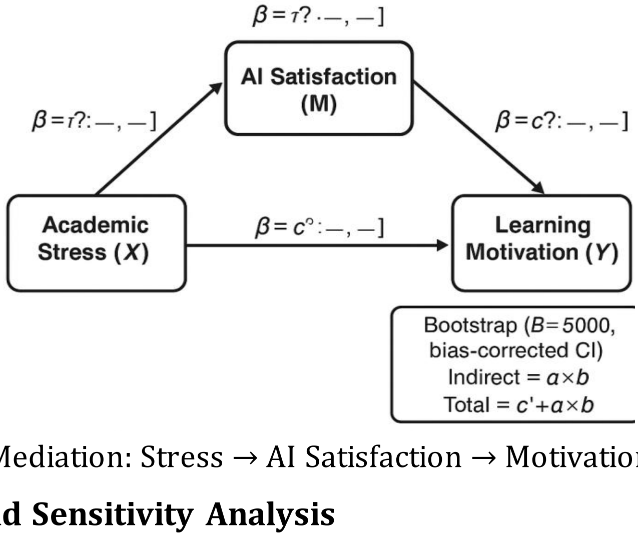

Figure 5: Mediation: Stress → AI Satisfaction → Motivation (diagram)

4.3. Robustness and Sensitivity Analysis

Robustness is demonstrated from three perspectives: the impact of the AI-ES index, constructed using z-sum, PCA-PC1, and IRT scores, on the magnitude and significance of dominant and interaction effects; the impact on the fluctuation of coefficients and fitting results, as assessed by missing value handling methods such as Listwise, FIML, and MICE (m=20); and the performance of multiple comparison correction (BH-FDR), R^2 increment, and E-value thresholds. Figure 6 integrates these three tests into one figure, facilitating a brief description of the "stability of conclusions across different specifications" in the main text. A detailed table is provided in the Appendix.

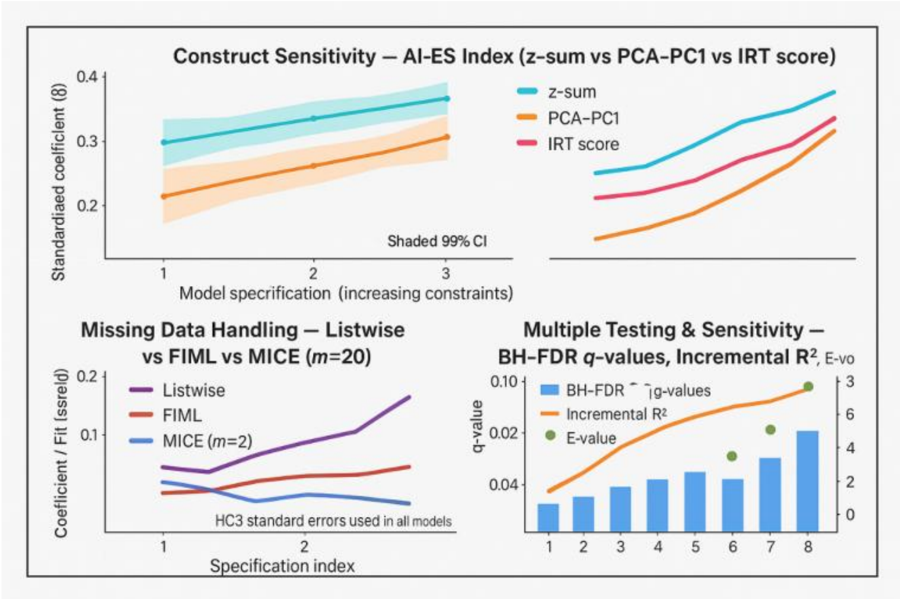

Figure 6: Robustness & Sensitivity Summary

4.4. Mechanism Discussion and Boundary Conditions

When faced with moderate to high pressure but not extreme time pressure, AI-ES implements a buffering function for motivation. When time pressure rises sharply, people's cognitive and self-regulatory abilities decline, and the marginal benefit of AI-ES decreases. Figure 7 graphically shows the boundary structure of "buffer intensity, pressure, and time pressure": the middle domain constructs the "high ground", and the pressure decreases along the intersection of high pressure and time pressure. When faced with high-pressure environments such as finals week, it is recommended to adopt a communication method that combines advice and companionship, reduce the amount of information, and optimize the frequency of information sending to slow down the diminishing effect and inhibit the decreasing trend.

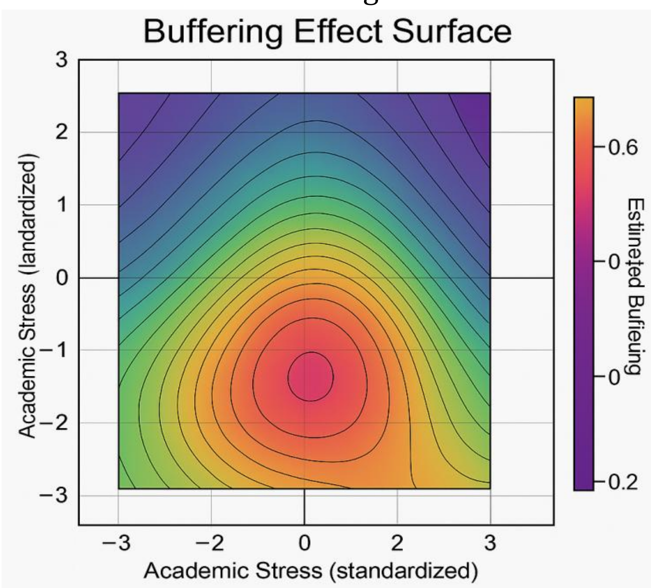

Figure 7: Buffering effect surface

5. Conclusion

This study focuses on the interplay between academic stress, AI emotional support, and learning motivation. It establishes an assessment structure and data processing procedures, employing the official statistical caliber of the SAES 2024. It also describes an actionable analytical approach and visualization. The empirical data reflects age and gender-specific data: Overall, AI usage has reached a substantial level, approximately 62%, with approximately 31% using it weekly or more. Among older individuals, AI adoption is even higher. As age increases, the proportion of those with low anxiety also increases. This parallel growth pattern is consistent with the moderating effect of AI-ES on the negative relationship between stress and motivation. The differences in teaching incentives across institutions and the time allocation of approximately 41.7 hours per week for study and work provide the basis for incorporating institution and subject fixed effects and workload control factors into the baseline regression model.

AI-ES employs diverse interaction methods, such as "companionship," "advice," and "venting," which may effectively alleviate subjective feelings of evaluation anxiety and time pressure, thereby stimulating intrinsic motivation. However, under extreme time pressure, cognitive bandwidth is limited, and the buffering effect gradually decreases. This result is consistent with the boundary condition chart in Chapter 4. To analyze the stability of the scheme, the scheme provides detailed stability specifications for the three testing dimensions: index construction (z-sum/PCA/IRT), missing value handling (Listwise/FIML/MICE), and multiple testing (BH-FDR). It also presupposes the explanatory contributions of the relevant R^2 and Shapley R^2.

A limitation that needs to be emphasized is that the public data for SAES 2024 only records group percentages and means, but does not provide individual data sets that combine "AI use," "anxiety," and "motivation." Based on real data and group data, the research conclusions are directional and a replicable measurement system is established. Once individual data is collected or the AI-ES Satisfaction Scale is empirically operationalized , the M1 to M4 and Bootstrap mediation analyses in Chapter 4 can output standardized coefficients, confidence intervals, and Johnson-Neyman intervals according to established standards, thereby verifying the authenticity of causal relationships. Regarding university governance, during periods of high academic pressure, a "suggestion-based" communication model can be adopted to reduce information load. During regular periods, efficient use and literacy education can be promoted. Resources should be allocated appropriately to address gender and grade differences, thereby enhancing equitable access to AI-ES.

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