# Economic Strain and Depressive Symptoms Among University Students in Bangladesh: A Quality-of-Life Study

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## Abstract

Economic comfort plays a significant role in ensuring students' quality of life. Measuring the economic condition of students in lower middle-income countries is a vital step in analyzing the impact of economic strain on quality of life. This study investigates the impact of cumulative economic strain on the mental health of a random sample of 500 undergraduate students of a private university in Bangladesh. Three self-reported and validated depression scales (BDI-II, PHQ-9, and CES-D) were used to analyze depressive symptoms, and a new Economic Strain Index (ESI) measured self-reported financial pressure, debt, and satisfaction with living conditions. More severe depressive symptoms are linked to students who experience greater economic strain, and female students are more likely to be impacted by the economic strain. The results suggest that the economic strain is consistently linked to increased depressive symptoms in all subgroups. The current study does not claim any causal relationship because of its cross-sectional design, nor does it claim generalizability given its limited study setting within one private academic institution. Campus-based financial assistance and mental health services, which also specifically focus on culturally sensitive, localized gender norms, could reduce depressive symptoms and enhance students' quality of life.

**Keywords:** economic strain; depressive symptoms; LMIC context; cross-instrument validation; student mental health; quality of life

## Introduction

Economic stability plays a significant role in shaping how young adults navigate their academic journey, and the quality of their lives [1–4]. Students who experience financial pressure, personal debt, or poor living conditions can experience depressive symptoms and lower well-being. This form of economic strain is infrequently measured with short-term indicators in university settings. Existing research mostly focuses on household or national stress indicators, leaving less attention to student-centered strain in lower-middle-income (LMIC) contexts [5]. Even though there is extensive literature exploring the role of economic strain and well-being among young-adult students, there is still limited work on exploring the economic strain as a formative cumulative index and precisely investigating how the economic strain impact various validated depressive scales in lower-middle-income country settings.

The current study focuses on a private academic institution in Bangladesh, where 500 undergraduate students self-reported their quality of life and responses to questions on socioeconomic conditions and mental health. The results from recent studies show that university students tend to report higher depressive symptoms with higher economic strain in addition to lack of family support, and resources [6,7]. Furthermore, studies also find that economic strain may operate differently across demographic groups and affect their quality of life, and that these effects are often moderated by gender and socioeconomic status [2,8–13]. Therefore, the current study investigates two core research questions. First, to what extent does a brief Economic Strain Index correspond to the severity of depressive symptoms measured across three validated scales among Bangladeshi undergraduate students? Second, to what extent do the associations between economic strain and depression differ by gender? The empirical analysis uses a three-stage analytical strategy to investigate the economic strain-depression link among Bangladeshi undergraduate students.

### *Related Literature*

Financial strain, academic pressure, and a lack of social support are all frequently associated with increased symptoms of anxiety and depression in research on university students' well-being. Studies conducted in Europe have shown this pattern across a variety of academic infrastructures and access levels contexts. National surveys conducted in Germany reveal a decrease in social connections and worries about the sustainability of academic support, both of which are linked to students' motivation and mood [14–16]. In the United Kingdom, student perceptions of online teaching quality and workload were associated with stress and depressive symptoms, suggesting that academic disruptions can shape daily experiences of well-being [17].

The empirical studies from Norway add further detail by showing how changes in learning environments and interaction patterns influence stress and coping among students [18,19]. Cross-national comparisons expand this picture. Recent cross-national and longitudinal studies show high levels of depression and anxiety across nine countries, emphasizing both shared stressors and local structural factors shaping student well-being [5,20]. Additional studies in European contexts show that academic pressure, loneliness, and financial uncertainty frequently interact, with implications for emotional health and quality of life among university students [21–25]. Economic strain is linked to poorer student mental health across various settings worldwide. UK studies have linked difficulty paying bills, debt exposure, and high financial worry to poorer psychological scores and declines over time [26–29]. During the pandemic, US data show that food insecurity and multiple hardships relate to worse mental health, even after adjustment [30]. Evidence from Bangladesh aligns with these larger findings while highlighting contextual differences. A nationwide cross-sectional survey during university closures documented high rates of depression and anxiety among students, with financial strain and institutional type playing important roles [6]. Earlier work with first-year students also reported substantial symptoms and identified socioeconomic stressors that interact with academic demands [7,26,27,31]. These studies indicate that strain is not only financial but also embedded in students' living arrangements, family resources, and access to support systems.

The existing research and its findings highlight three key gaps that the current study aims to address. Firstly, economic strain is a significant factor affecting students' emotional well-being, academic engagement, and performance. Secondly, existing research often uses broad stress or income measures rather than specific, brief economic strain indicators that closely align with students' current lived experiences. Thirdly, gender differences are often noted, but how strain affects male and female students in LMIC settings remains less well explored. These underexplored themes justify the development of a novel, brief economic strain index (ESI) to assess economic strain as an indicator of quality of life and examine its relationship with depressive symptoms, using multiple measurement tools in a lower-middle-income context.

### *Theoretical framework and hypotheses*

The study draws on three complementary theoretical frameworks. In this study, "traditions" refers to established lines of research which present balancing explanations of how economic strain influences mental health conditions. The stress process tradition posits that material strain and role pressures increase psychological distress by depleting coping resources [24,32]. The social determinants tradition locates these strains in everyday economic conditions that influence exposure and vulnerability [25,33]. The conservation of resources perspective posits that resource depletion exerts a greater effect than resource acquisition, leading to prolonged shortages and enduring symptoms [33,34]. All of these traditions support the idea that strain exposure results from a combination of stressors rather than one fundamental characteristic. Financial strain, debt, and discontent with living conditions are just a few of the stressors that the Economic Strain Index (ESI) compiles and uses as the exposure of interest. After controlling for age, gender, socioeconomic status, sleep patterns, and hours of social engagement, the first research question (RQ1) asks how much cumulative strain predicts the severity of depressive symptoms on three validated scales . The second research question (RQ2) asks whether gender influences this relationship within the same models. The current study makes the following three hypotheses after a thorough review of the literature and analysis of related studies:

***(H1):***

Higher economic strain is associated with more severe depressive symptoms across the three scales.

***(H2):***

Economic strain has a stronger association with depressive symptoms for female students than for male students.

***(H3):***

The positive association between economic strain and depressive symptoms remains consistent across inferential, structural, and predictive approaches.

## Methods

### *Study setting and sample*

The data come from an anonymized group of 500 undergraduate students at a private university in Dhaka, Bangladesh, drawn from the "Mental Health of Undergraduate Students in Bangladesh" dataset. The dataset was created in 2024 by researchers at Daffodil International University to document student well-being, living conditions, and economic pressures alongside validated depression scales [35]. Because the sample comes from one private institution, the results speak most directly to similar university settings and should not be treated as nationally representative. The questionnaire covers demographic characteristics, student-life experiences, and validated depression scales, and the instrument file details the relevant sections and response formats [35].

### *Measures*

Dependent variables (depression outcomes): The data collection strategy measures depressive symptoms with three validated scales: the Beck Depression Inventory-II (BDI-II), the Patient Health Questionnaire-9 (PHQ-9), and the Center for Epidemiologic Studies Depression Scale (CES-D). BDI-II captures symptom severity, PHQ-9 captures DSM-aligned symptoms over the past two weeks, and CES-D captures symptom frequency over the past week. The study uses three measures specifically the BDI-II, PHQ-9, and CES-D, to evaluate whether the association between economic strain and depressive symptoms holds across complementary instruments. Higher scores indicate more severe symptoms on each scale.

Primary independent variable: Economic Strain Index (ESI). We use a short set of concrete, student-relevant indicators to capture day-to-day financial pressure reported directly by students. The study introduces a new formative Economic Strain Index (ESI) as the primary independent variable to measure the overall economic worries among Bangladeshi undergraduate students. It combines three binary variables: financial pressure, personal debt, and dissatisfaction with the living environment, and scales the resulting score to 0-1 (ESI_norm). Structure tests on the full sample show KMO = 0.530 and Bartlett's test $p < 0.001$. This KMO statistic is methodologically appropriate because the index is designed as a formative composite of distinct stressors rather than a reflective latent construct. A one-factor solution loads all three items as expected, with financial pressure loading most strongly; the PCA loadings are positive for all items. KMO (Kaiser–Meyer–Olkin) checks whether the items share enough common pattern to combine into one index, and Bartlett's test checks whether the items are meaningfully correlated. Both tests support summarizing the three items as one economic strain measure. Figure 1 shows the distribution of ESI_norm against three main dependent variables in this study, with most cases at 0.33 and 0.67. Additional data preprocessing reveals that the Spearman correlations, with ESI following the expected direction, align with the three depression outcomes and covariates. Robustness checks confirm consistent results. A factor-scaled ESI ranks students similarly and yields comparable effects. Leave-one-item-out and weighted versions maintain the same sign and magnitude. Different binning methods for descriptive plots do not change the overall trend. ESI_norm is the normalized index (scaled from 0 to 1), with higher values indicating greater economic strain. These cut points reflect low, mid-range, and high strain within the sample and support clear descriptive comparisons.

**Covariates**. Age (years), gender (male = 0, female = 1), subjective socioeconomic status (ordered levels), typical sleep hours, and typical social hours are obtained from the student life section. The instrument file lists response options used to code these fields.

### *Missing data and preprocessing*

The raw bilingual labels are mapped to programmatic names, fields are converted to numeric types, and ordinal categories are maintained. After specific recodes and checks, the analytic file includes N = 500. Variance inflation factor (VIF) values are close to 1.0, indicating no multicollinearity issues. Brief median imputations address small gaps in ordinal fields. The descriptive Figure 1 illustrates the sample composition (ESI four-point distribution) and aligns with the data presented in Table 1.

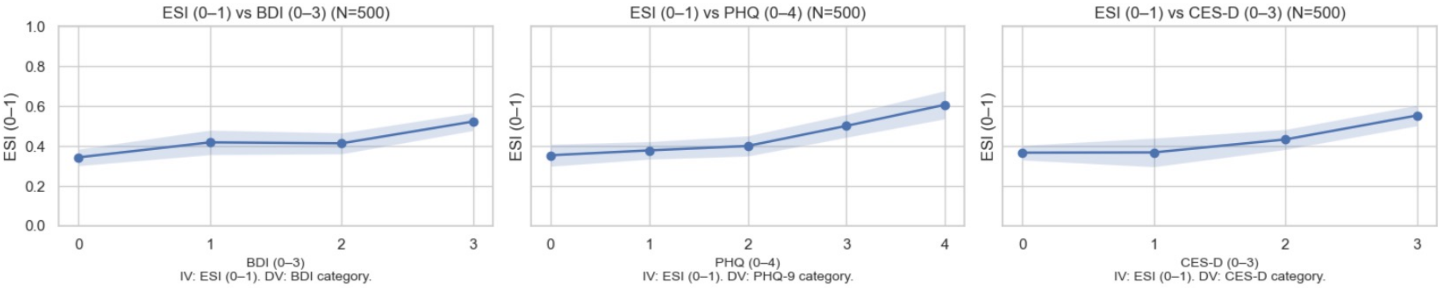


**Figure 1.** Three panels showing class balance and Mean ESI by DV category (95% CIs) for BDI-II, PHQ-9, CES-D.

The category profile exhibits headroom across outcomes. BDI is most frequently at minimal severity, PHQ-9 at mild, and CES-D at minimal. ESI spans the entire range, with the largest groups at 0.33 (41.8%) and 0.67 (30.4%), and a smaller high-strain group at 1.00 (7.2%). Female participants make up 28.6% of the cohort, while male participants comprise 71.4%. These distributions justify the use of ordered models and a latent approach, and they motivate the ESI trend panels. Figure 3 shows mean outcome levels with 95% confidence intervals across quantiles of continuous ESI; the panels illustrate graded risk and help guide the reader through the inferential tests.

***Analytic plan***

The study employs three linked analyses to address the two core research questions. First, we fit ordered logistic regression models to estimate the association between a one-unit increase in economic strain and moving into a higher depression severity category, holding covariates constant. Second, we fit a structural equation model (SEM) that combines the three depression scales into one latent depression factor. Third, we use a machine-learning classifier as a robustness check to determine whether economic strain remains a top predictor when the objective is prediction rather than inference.

***Analytic strategy***

In the second step, a structural equation model treats BDI-II, PHQ-9, and CES-D as ordinal indicators of a single latent Depression factor. This latent factor is then regressed on ESI_norm and the same set of covariates, with gender again allowed to modify the effect of strain. This framework places all three instruments on a standard scale, accounts for measurement error, and tests whether the economic strain pathway remains when depression is modeled as a unified construct rather than three separate outcomes. Model evaluation utilizes standard fit indices for categorical SEM (i.e., CFI, TLI, RMSEA with confidence interval, and SRMR), as well as standardized loadings and paths.

***Machine learning robustness check***

In the third step, a multiclass XGBoost classifier predicts depression severity categories based on ESI_norm and the covariates, using a stratified train–test split with class-balanced weights. This step does not aim to create a clinical screening tool; instead, it provides a predictive cross-check of feature importance in a non-linear context. Performance metrics (i.e., accuracy, macro-F1, and quadratic weighted kappa) evaluate how well the model reproduces the ordered categories, and permutation-based SHAP values rank features by their average contribution to predictions. If ESI_norm is a strong predictor in the ordered logit models, it remains a key factor in the latent Depression construct in SEM, and ranks among the top features according to

**Table 1.** Summary of measures and response distributions (N=500)

| Variable (role) | Code | Response label | % |
|---|---|---|---|
| BDI_score (Primary DV) | 0 | Minimal depression | 33.0 |
| | 1 | Mild depression | 16.2 |
| | 2 | Moderate depression | 22.4 |
| | 3 | Severe depression | 28.4 |
| PHQ_score (Primary DV) | 0 | Minimal depression | 21.2 |
| | 1 | Mild depression | 30.6 |
| | 2 | Moderate depression | 21.6 |
| | 3 | Moderate-severe depression | 13.8 |
| | 4 | Severe depression | 12.0 |
| | — | Missing | 0.8 |
| CESD_score (Primary DV) | 0 | Minimal or no depressive symptoms | 43.8 |
| | 1 | Mild depression | 13.0 |
| | 2 | Moderate depression | 21.0 |
| | 3 | Severe depression | 22.2 |
| ESI_norm (Primary IV) | 0 | 0.00 (formative composite of financial pressure, debt, and living-environment dissatisfaction) | 20.6 |
| | 1 | 0.33 | 41.8 |
| | 2 | 0.67 | 30.4 |
| | 3 | 1.00 | 7.2 |
| Gender_binary (Control) | 0 | Male | 71.4 |
| | 1 | Female | 28.6 |
| SES_encoded (Control) | 1 | Lower | 3.4 |
| | 2 | Lower-Middle | 14.2 |
| | 3 | Middle | 65.6 |
| | 4 | Upper-Middle | 15.8 |
| | 5 | Upper | 1.0 |
| Sleep_hours_num (Control) | 1 | Below 5 hours | 18.4 |
| | 2 | 5 hours | 18.6 |
| | 3 | 6 hours | 32.2 |
| | 4 | 7 hours | 17.8 |
| | 5 | 8 hours | 10.2 |
| | 6 | More than 8 hours | 2.8 |
| Social_hours_num (Control) | 1 | < 2 hours/day | 16.0 |
| | 2 | 2–4 hours/day | 44.4 |
| | 3 | 5–7 hours/day | 26.2 |
| | 4 | 8–10 hours/day | 7.8 |
| | 5 | > 10 hours/day | 5.6 |

SHAP. The triangulation supports the idea that cumulative economic strain is a central driver of depressive symptoms in this group. The following sections present and compare results from these three modelling approaches. We treat this as a robustness check: we train the model with repeated cross-validation and report out-of-sample accuracy, then use permutation SHAP values to rank which predictors contribute most to correct classification.

## Results

### *Ordered Logistic Models*

Table 2 presents six ordered logistic regression models: a main-effects model and an ESI × gender model for each depression scale (BDI-II, PHQ-9, CES-D). All models include ESI_norm as the primary predictor and adjust for age, gender, socioeconomic status, hours of sleep, and hours of social activity. The descriptive ESI trend panels show a steady increase in symptom levels with increasing strain, consistent with the regression estimates.

Across all three scales, the main-effects models support (H1). As economic strain increases from the lowest to the highest level (0 to 1 on ESI_norm), the odds of being in a worse BDI category rise by a factor of approximately 4.47. Similarly, odds are about 4.67 times higher for PHQ-9 and 4.36 times higher for CES-D, even after controlling for other factors. These figures indicate roughly a four-fold increase in the likelihood of experiencing more severe depressive symptoms across different measurement tools.

The interaction models do not support (H2), as the (ESI_norm × gender) interaction terms cluster near 1.00 (approximately 1.05–1.12), have wide confidence intervals, and are not statistically significant. Model fit remains consistent. However, gender shows a clear baseline difference: at the same ESI level, female students have roughly 50–95% higher odds of being in more severe categories compared to male students. The ordered models, therefore, suggest a gendered baseline gap but a similar economic-strain slope. Control variables behave as expected: higher socioeconomic status and more sleep correlate with lower odds of severe symptoms, while more social hours correlate with higher odds, especially in the top CES-D categories. Age shows minimal association. These factors do not significantly diminish the economic-strain effect.

Proportional-odds assessments indicate that BDI-II satisfies the assumption, with stable ESI coefficients across thresholds. For PHQ-9 and CES-D, the ESI effect is stronger at the most severe categories, suggesting slight violations of the proportional odds assumption. Sensitivity analyses with partial proportional-odds and adjacent-category models reveal the same main trend: ESI_norm consistently predicts positively, and the interaction remains non-significant. These results justify proceeding with a latent-variable test as the next step.

### *Structural Equation Modeling (SEM)*

The SEM treats BDI-II, PHQ-9, and CES-D as ordinal indicators of a single latent Depression factor (Figure 2). All three scales load strongly on this factor, with standardized loadings ranging from 0.91 to 0.96. Model fit is excellent (CFI and TLI are approximately 1.00, RMSEA is around 0.00, and SRMR is low), supporting the assumption of a shared underlying construct. The regression of the latent factor on ESI_norm and the covariates reinforces the main-effects pattern. The standardized path from ESI_norm to Depression is about $\beta \approx 0.24$ (unstandardized approximately 0.97, $p < 0.001$). A one-standard-deviation increase in ESI_norm corresponds to roughly a 0.24-standard-deviation rise in latent depression, which is a larger effect than paths from sleep, SES, social hours, or age. Sleep and SES show protective paths; social hours and gender display positive paths; age is nearly zero. Allowing the ESI to Depression path to vary by gender does not improve model fit, and the moderating path remains small and non-significant. As with the ordered models, gender shifts the baseline level but does not affect the strength of the ESI slope. The SEM thus supports (H1) and again does not support (H2). Along with the strong loading structure, these results provide compelling evidence for (H3): the effect of economic strain persists when the three scales are combined into a single construct.

### *Predictive Ranking*

The final step employs a multiclass XGBoost classifier and permutation-based SHAP values as a predictive cross-check (Figure 3). Each model predicts depression category from ESI_norm and covariates using a stratified train–test split with class-balanced weights. Predictive performance is modest: accuracy is 0.24 for BDI (baseline 0.33), 0.31 for PHQ-9 (baseline 0.31), and 0.34 for CES-D (baseline 0.44), with macro-F1 scores around 0.22–0.30. These results indicate that the models do not provide strong classification and are not suitable for screening. Consequently, this machine-learning approach was strictly deployed as an exploratory tool to extract SHAP values for non-linear feature ranking, not as a clinical diagnostic classifier. However, the SHAP rankings are consistent. For BDI-II, ESI_norm is the second most important feature (after sleep hours). For PHQ-9 and CES-D, ESI_norm is one of the top-ranked feature, surpassing age, sleep, and social hours. Therefore, even in a non-linear setting with modest accuracy, economic strain remains a key driver of predicted depression severity. Thus, predictive ranking supports both (H1) and (H3) for the current study.

Across the three approaches, the Economic Strain Index has profound effects on student mental health and well-being. In stage one, the ordered logit models show

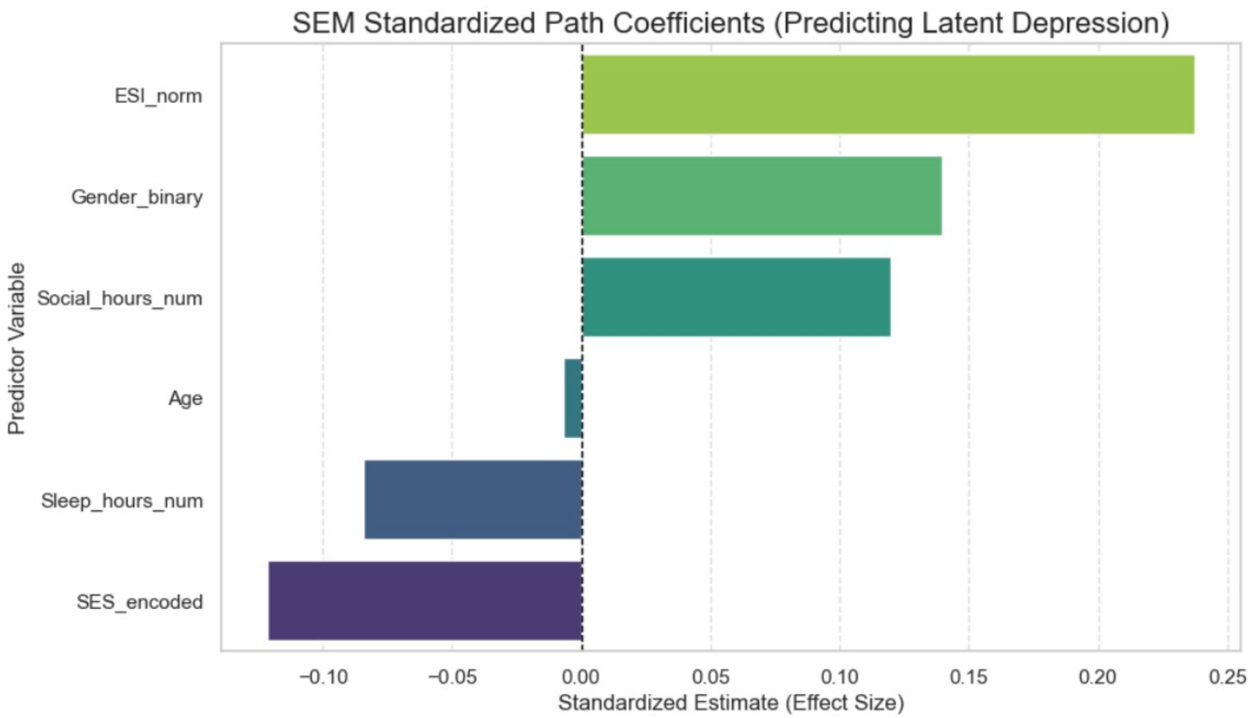


**Figure 2.** SEM path diagram with standardized loadings and paths.

that moving from the lowest to the highest level of economic strain results in a three to fourfold increase in the odds of being in worse depression categories. In stage two, the SEM highlights that a one-standard-deviation increase in ESI_norm is associated with about a 0.24-standard-deviation rise in a common depression factor. Finally, the XGBoost–SHAP results show that ESI_norm consistently ranks among the top features across all three outcomes. Therefore, the findings from all three approaches support (H1) and (H3) such that economic strain is strongly and consistently linked to depressive symptoms across multiple analytical approaches. Although there is no clear evidence supporting (H2), gender differences are evident in baseline levels. Overall, the triangulation highlights cumulative economic strain as a key quality-of-life factor for students in this setting.

## Discussion

The core aim of this study is to investigate whether an Economic Strain Index can predict depression severity among university students in Bangladesh and whether gender influences this relationship. Across all three validated depression scales, ordered logistic models indicate that increasing from ESI_norm = 0 (lowest strain) to ESI_norm = 1 (highest strain) is associated with a 3.3–3.7-fold rise in the odds of being in a higher depression category, after adjusting for age, gender, socioeconomic status, sleep, and social hours. The second analytical strategy, SEM, also confirms this pattern: a one-standard-deviation increase in ESI_norm corresponds to roughly a 0.24-standard-deviation rise in a latent Depression factor that combines BDI-II, PHQ-9, and CES-D. XGBoost–SHAP rankings identify ESI among the top one or two predictors, despite modest overall accuracy. Overall, these findings support (H1) and (H3).

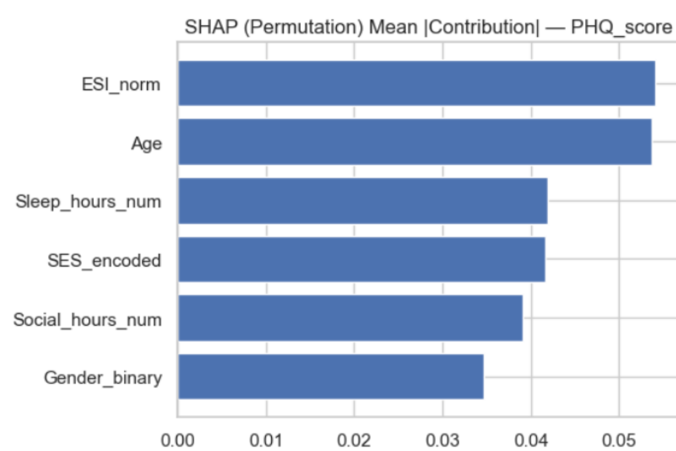


**Figure 3.** SHAP feature importance (mean ISHAPI).

**Table 2.** Convergent evidence on the effect of the Economic Strain Index (ESI_norm) across modeling strategies

| Outcome / construct | Model type | ESI_norm effect (metric) | Approximate impact / size | Other key patterns and role in triangulation |
|---|---|---|---|---|
| BDI-II severity category | Ordered logit (H1 main-effects) | OR = 4.47, 95% CI [2.44, 8.20], $p < 0.001$ | ≈ 4.47x higher odds of worse BDI category (0 to 1 change in ESI) | Female gender OR = 1.95; higher SES and more sleep protective; more social hours harmful. Supports H1; baseline gender gap, common strain slope. |
| PHQ-9 severity category | Ordered logit (H1 main-effects) | OR = 4.67, 95% CI [2.55, 8.58], $p < 0.001$ | ≈ 4.67x higher odds of worse PHQ category | Female gender OR = 1.50; SES and sleep protective; social hours harmful. Strongest ESI odds ratio of the three scales. Proportional odds partly drift at upper cuts. |
| CES-D severity category | Ordered logit (H1 main-effects) | OR = 4.36, 95% CI [2.35, 8.07], $p < 0.001$ | ≈ 4.36x higher odds of worse CES-D category | Female gender OR = 1.60; SES and sleep protective; social hours harmful. Proportional odds show stronger ESI effects at highest CES-D levels. |
| Latent Depression factor | SEM (structural path from ESI) | Standardized path $\beta$_ESI to Depression = 0.237 (unstd Estimate = 0.97, $p < 0.001$) | +0.24 SD higher latent depression per 1 SD increase in ESI_norm | BDI, PHQ-9, CES-D load very highly on Depression (Std. loadings ≈ 0.91–0.96). Fit excellent (CFI/TLI ≈ 1.00; RMSEA ≈ 0). ESI has the largest structural path among predictors. |
| BDI-II severity category | XGBoost + SHAP | Mean SHAP for ESI = 0.065 | 2nd highest feature impact (after sleep hours) | Shows a prominent rightward shift for the Economic Strain Index, driving BDI-II severity predictions. |
| PHQ-9 severity category | XGBoost + SHAP | Mean SHAP for ESI = 0.054 | 2nd highest feature impact (after age) | Shifts to the second-highest position after age for PHQ-9 symptom classification. |
| CES-D severity category | XGBoost + SHAP | Mean SHAP for ESI = 0.068 | 2nd highest feature impact (after age) | Shifts to the second-highest position after age for CES_D symptom classification. |

These results are consistent with the stress process, social determinants, and conservation of resources traditions, all of which suggest that cumulative financial pressure, debt, and poor living conditions increase psychological distress. Specifically, these findings align with the conservation of resources theory by demonstrating how the cumulative depletion of fundamental material security elevates baseline depressive symptoms. The formative ESI index, constructed from concrete stressors rather than assumptions, functions as intended: higher scores indicate greater depressive severity across various instruments and analytical methods. The findings expand on prior Bangladeshi research linking economic hardship, institutional context, and academic pressure to student mental health. The findings support prior research showing that financial stress and unstable learning environments harm educational well-being. The effects vary across identities such as gender, socioeconomic status, language, and social positions, where precarious visa statuses and unexpected health crises can further exacerbate students' exposure to strain and limit access to support [8,12,13,36–42].

The primary contribution of the current study, consequently, is building a novel and brief economic strain index (ESI) that captures the localized nuances and then tests whether economic strain has any significant association with depressive symptoms through validated scales. The findings suggest that the formative ESI is strongly associated with all the validated depressive symptom scales, and gender differences reveal a clear baseline pattern: women have 50–95% higher odds of being in worse depression categories than men at the same ESI level, and SEM indicates higher latent depression levels as well. However, the ESI slope does not differ by gender, which does not support (H2). Economic strain seems to operate through a shared mechanism, with women starting from a higher baseline level. Therefore, the evidence suggests that financial strain is a key indicator of student mental health in this context, and gender reflects baseline vulnerability rather than differential sensitivity to strain.

### *Policy Implications*

The findings from the current study recommend that student mental health policy and academic financial policy should be part of a cohesive policymaking process rather than separate discussions. Some recommended options for improving undergraduate students' health and well-being include targeted scholarships, well-designed fee relief, and short-term emergency grants that reduce immediate economic pressure, along with structured work–study programs that pay fair wages, protect study time, and reduce reliance on unstable off-campus jobs. Subsequently, additional important measures that support sleep and basic counseling, such as reasonable class schedules, careful exam clustering, quiet hours in hostels, and brief, focused counseling, may complement financial efforts by addressing smaller but consistent factors linked to depressive symptoms.

The study also acknowledges that, as a private academic institution in an LMIC setting, allocating more focused resources and dedicated support to improve students' financial well-being and ensure better mental health, lower depressive symptoms, and an overall improved quality of life is not easy. Therefore, additional planning and long-term planning are needed to have such a foundational space to foster resource allocation and discussion among young people. Furthermore, universities may consider gender-responsive supports that reduce barriers to help-seeking and safety. Examples include safe and accessible campus spaces, access to trained counselors who can meet students' needs, and clear reporting and referral pathways. These steps align with the study's findings without implying causal effects beyond the observed associations.

### *Limitations*

There are several limitations to consider when interpreting these findings. First, the cross-sectional design and reliance on self-reported survey data preclude establishing causality. Notably, the relationship between financial difficulties and mental health may be bidirectional; while economic strain can exacerbate depression, students already experiencing higher depressive symptoms might also perceive and report their financial struggles more negatively due to reporting bias. Second, the sample is drawn from a single private university in Dhaka, which restricts the generalizability of the results to public universities or regional campuses. Third, the Economic Strain Index (ESI) used is a brief three-item measure that, while covering core aspects of financial pressure, debt, and housing dissatisfaction, may not capture the full spectrum of economic stressors. Statistically, partial deviations from proportional odds for the PHQ-9 and CES-D at the highest categories suggest more complex patterns among the most severe cases. Finally, the machine-learning models demonstrated limited accuracy and macro-F1 scores that did not surpass simple baselines; consequently, SHAP results were utilized strictly to rank feature importance at the population level rather than for individual clinical predictions.

## Conclusion

The findings strongly suggest that across all three depression measures and several analytical techniques, a simple Economic Strain Index that incorporates financial strain, personal debt, and living environment dissatisfaction is consistently linked to more severe depressive symptoms. More specifically, the findings support a strong association rather than a causal claim, given the cross-sectional design. This pattern is particularly noticeable in a lower-middle-income setting, where family resources may be strained, and formal financial safety nets are not robust or stable, which also aligns with theoretical frameworks on stress, social determinants, and resource loss.

Furthermore, the study also finds that women at the same strain level have higher baseline depression levels, which emphasizes the significance of taking gender into account when developing financial and mental health policies and making sure that those who are initially at higher risk receive financial assistance. Future research should expand this approach across multiple universities, incorporate longitudinal data, and evaluate targeted interventions to lower ESI scores. Meanwhile, the clear message for universities and policymakers is to reduce economic strain through scholarships, fee waivers, structured work–study programs, and supportive learning environments, practical strategies to enhance student mental health.

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**Ethics Approval.** The original survey followed institutional and national guidelines for research with human participants and received ethics approval from the host institution. The current analysis uses anonymized, publicly available data and was exempt from further review.

**Data Availability.** The anonymized undergraduate mental-health dataset is available through Mendeley Data (DOI: 10.17632/f4z2bfv7vk.1). The instrument file and variable descriptions accompany the dataset. The full Python code, in a Jupyter notebook, is also available with the journal as additional materials for transparency, replicability, and research rigor.

**Competing Interests.** The author declares no competing interests.

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### *AI Statement*

The author declares that AI was used in line with the MJGH AI policy. Gemini Thinking was used to fix grammar and improve readability. All text generated was reviewed by the author.