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Academic Setbacks and Contributing Factors Among Computing Students in Philippine Higher Education

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ABSTRACT

Academic setbacks such as incomplete (INC) grades and course failures remain persistent challenges to student retention in information technology programs in Philippine state universities. It is critical to distinguish between these two academic statuses: an INC grade signifies that a student has completed substantial coursework but has unfinished requirements due to valid, often extenuating, circumstances, whereas a failing grade denotes that the student did not meet the minimum academic standards for the course (Romero & Ventura, 2020). Adopting a proactive, preventive approach, this study analyzed contributing factors, support system utilization, and emotional impacts among 101 computing students at a state university in the Philippines using a validated structured survey. Quantitative techniques such as descriptive statistics, Spearman correlation, one-way ANOVA, chi-square, and multiple linear regression were applied. Financial difficulties (M=3.22), heavy course load (M=3.14), and time management issues (M=3.10) were the top-rated contributors. A regression model explained 37% of stress variance ($R^2=0.370$; $F(15,72)=2.82$, $p=.002$), with lack of resources ($\beta=0.433$), work commitments ($\beta=0.320$), and subject difficulty ($\beta=0.303$) as significant predictors. Second-year students showed significantly higher resource and connectivity barriers across all ANOVA factors ($p<.05$, $\eta^2=0.07–0.12$). Findings support the development of data-driven early warning systems and proactive academic advising frameworks within computing programs.

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INTRODUCTION

Educational data analytics has emerged as a transformative approach for understanding and addressing student academic challenges in higher education. Institutions that systematically analyze student performance data can identify at-risk trajectories early and design targeted interventions before academic setbacks compound into dropout or prolonged program delay.

Accordingly, Namoun and Alshanqiti (2021) demonstrated through a systematic review of 62 studies that regression-based and machine-learning models consistently identify socioeconomic constraints, prior academic standing, and course engagement as the dominant predictors of student performance—findings that directly contextualize the present study's analytical approach. Similarly, Albreiki et al. (2021) confirmed that educational data mining provides actionable identification of at-risk students when applied to primary institutional data, enabling timely advising outreach and resource reallocation.

Within the College of Computing and Information Sciences at a state university in the Philippines *(institution anonymized to protect academic integrity and student confidentiality)*, a notable proportion of students encounter incomplete (INC) or failing grades during their academic journey. It is imperative to distinguish that an INC grade represents a distinct academic status from a course failure; an INC indicates that a student has completed substantial coursework but has unfinished requirements due to extenuating circumstances, whereas a failing grade indicates that course requirements were not met (Romero & Ventura, 2020). In the Philippine context, where state universities offer free tuition under the Universal Access to Quality Tertiary Education Act, student attrition persists at rates approaching 35%, driven not by tuition costs but by hidden barriers—transportation, materials, and connectivity (Gutiérrez-de-Rozas et al., 2022; Pelima et al., 2024). Despite this, limited empirical work has examined the specific antecedents and emotional consequences of INC grades and failures in computing programs using locally collected survey data. This study bridges that gap by applying multiple quantitative techniques to survey data collected directly from computing students, with the aim of identifying key factors influencing academic recovery and providing evidence-based recommendations for institutional support design.

OBJECTIVES OF THE STUDY

This study aimed to analyze the contributing factors to academic setbacks among computing students in Philippine higher education and to identify the key factors that significantly influence learning outcomes. Specifically, it seeks to determine the demographic and academic profiles of computing students, including those who experienced incomplete grades or course failures in the previous semester, and to identify the primary factors contributing to these academic setbacks.

Furthermore, this study examines the utilization of support systems among students experiencing academic difficulties and assesses the emotional impact of these setbacks on their well-being. It also aims to determine whether there are significant differences in contributing factors across year levels, identify predictors of stress and pressure among students with academic setbacks, and ultimately provide data-driven recommendations that can support academic advising, intervention design, and institutional decision-making.

(Note: The null hypotheses tested were: H_{01}—no significant year-level differences in contributing factors to academic setbacks; H_{02}—no significant association between work status and incomplete grade experience; and H_{03}—contributing factors do not significantly predict student stress levels.)

CONCEPTUAL / ANALYTICAL FRAMEWORK

This study was guided by an educational data analytics framework adapted from Romero and Ventura (2020), which systematically transforms raw educational data into meaningful insights for institutional decision-making, as shown in Figure 1.

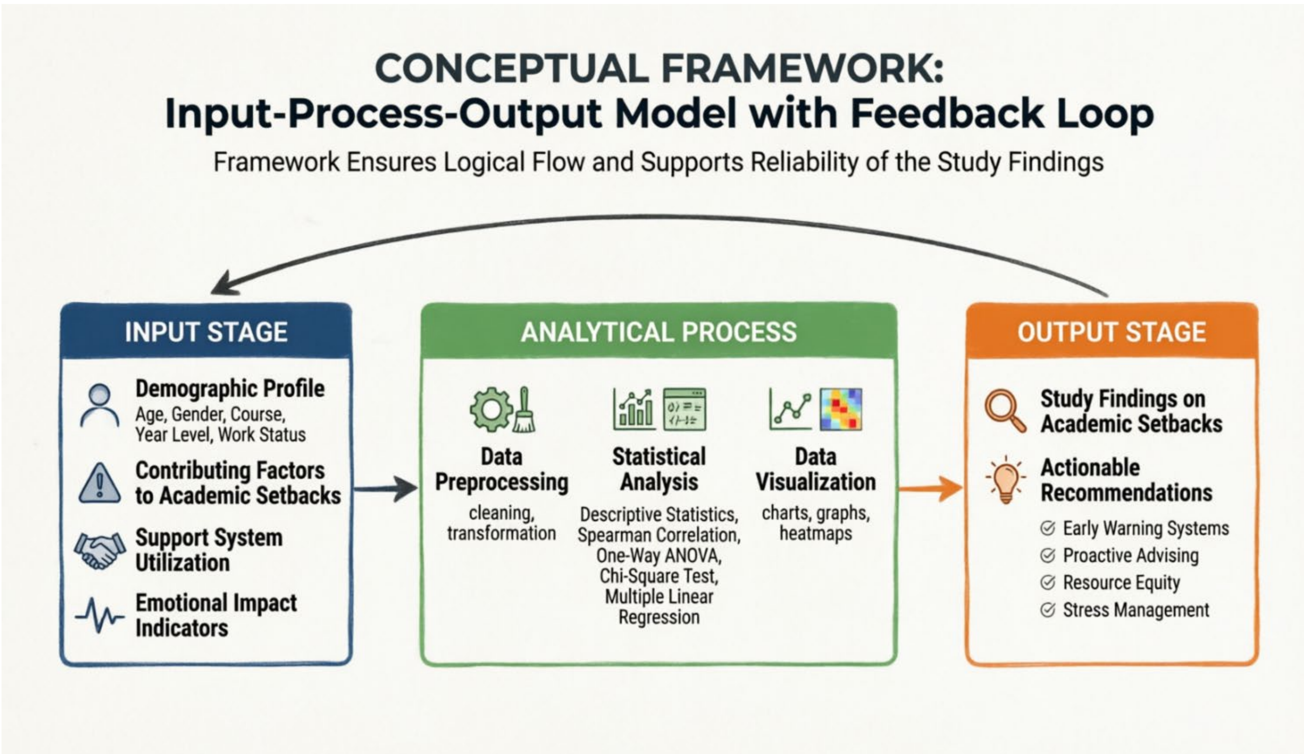

Figure 1. Conceptual Framework

Figure 1 shows the general outline of this study. The **input stage** involved survey data collection from computing student respondents, measuring: (1) contributing factors to academic setbacks (financial difficulties, heavy course load, time management issues); (2) support system utilization (family support, library resources, online learning services); (3) emotional impact indicators (stress/pressure, motivation to improve, determination to succeed); and (4) demographic variables (Age, Gender, Course, Year Level, Work Status).

The **analytical process stage** employed structured data analysis through data preprocessing (cleaning and transformation), statistical analysis including Descriptive Statistics, Spearman Correlation Analysis, One-Way ANOVA with Eta-squared, Chi-Square Test of Independence, and Multiple Linear Regression, complemented by data visualization through charts, graphs, and heatmaps.

The **output stage** generates study findings and actionable recommendations for institutional support. The desired outcome is to provide practical recommendations including early warning systems for at-risk students, targeted interventions, enhanced resource allocation, academic support programs, and data-driven decision making. The feedback loop ensures that findings continuously inform future data collection and institutional policy improvements.

MATERIALS AND METHODS

Research Design and Respondents

This study employed a cross-sectional quantitative research design. Primary data were collected through a structured survey administered to undergraduate students across all four BSIT, BSIS, BSEMC, and BLIS programs. Total enumeration was initially attempted among all eligible computing students, yielding 108 intended responses. After data screening for completeness, seven responses were excluded due to incomplete data (missing >20% of survey items), resulting in an actual valid sample of 101 respondents. The sample has a near-equal gender split (49.5% female, 49.5% male), predominantly first-year students (50.5%), and mostly not engaged in paid work (93.1%).

Methodological Justification for Sample Size and Scope

A critical methodological clarification is required regarding the sample size. While only 11 students (5 with INC, 6 with failing grades) reported actual academic setbacks in the previous semester, restricting the study solely to these 11 students would yield statistically insufficient data for robust multivariate analyses such as regression and ANOVA. Therefore, the survey was administered to the entire population of 101 computing students. This proactive approach aligns with Educational Data Mining (EDM) principles (Romero & Ventura, 2020), which emphasize identifying systemic risk factors and early warning indicators across the general student population *before* formal academic setbacks occur. By surveying the broader population, this study assesses the prevalence of contributing factors that predispose students to academic setbacks, rather than merely retrospectively analyzing those who have already failed.

Instrument and Validation

The survey instrument covered three domains rated on a 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree): (1) factors contributing to academic setbacks; (2) support system utilization; and (3) emotional impacts of academic setbacks. The scale was interpreted as follows: 1.00–1.80 = Very Low; 1.81–2.60 = Low; 2.61–3.40 = Moderate; 3.41–4.20 = High; 4.21–5.00 = Very High. Content validity was established by three experts in information technology education using a Content Validity Index (CVI≥0.80). Internal consistency yielded Cronbach's alpha values of $\alpha=0.87$ (contributing factors), $\alpha=0.83$ (support systems), and $\alpha=0.81$ (emotional impact), all exceeding the 0.70 threshold.

Validation and Parameters of Academic Setbacks

To ensure data accuracy, respondents were explicitly instructed to refer to their official student portals and grading sheets from the previous semester when reporting their INC or failing grades. The parameters for these grades encompassed all academic subjects taken during the previous semester, including both major specialization courses and general education subjects. However, due to the anonymous nature of the data collection and strict compliance with the Data Privacy Act of 2012 (RA 10173), individual transcript verification by the researchers was not conducted. Consequently, while steps were taken to prompt accurate recall, self-reporting bias is acknowledged as a limitation of this study.

Data Collection and Preprocessing

Survey data were gathered via an online form distributed through official college channels. Respondents were briefed on the study's purpose and their voluntary participation. Data were cleaned, checked for outliers, and encoded into a secure database. Categorical variables were standardized; Likert responses were checked for normality. The regression analysis used complete-case data (n=88 after listwise deletion). The study complied with the Data Privacy Act of 2012 (RA 10173).

Analytical Techniques

Descriptive statistics (mean, SD, frequency, percentage) summarized all variables. Spearman rank correlation examined relationships between contributing factors and emotional outcomes. One-way ANOVA with Eta-squared and Tukey HSD post-hoc tests compared year-level differences. Chi-square with Cramer's V tested work status and INC associations. Multiple linear regression (OLS) identified predictors of stress/pressure. All analyses used Python-based statistical libraries (pandas, scipy, statsmodels). Significance was set at $\alpha=0.05$.

RESULTS AND DISCUSSION

Demographic Profile

Table 1 presents the demographic characteristics of the 101 respondents. The sample was evenly distributed across age groups (18–21+) and gender, dominated by BSIT (45.5%) and BLIS (41.6%) enrollees, with first-year students comprising 50.5%. Only 6.9% were engaged in part-time work, and 5.0–5.9% reported INC grades or subject failures.

Table 1. Demographic Characteristics of CCIS Student Respondents (N=101)

Variable	Category	n	%
Age	18 and below	24	23.8
	19	27	26.7
	20	25	24.8
	21 and above	25	24.8
Gender	Female	50	49.5
	Male	50	49.5
	Prefer not to say	1	1.0
Course	BSIT	46	45.5
	BLIS	42	41.6
	BSIS	9	8.9
	BSEMC	4	4.0
Year Level	1st Year	51	50.5
	2nd Year	33	32.7
	3rd Year	16	15.8
	4th Year	1	1.0
Work Status	Not working	94	93.1
	Part-time	7	6.9
Incomplete Grade	No	96	95.0
	Yes	5	5.0
Failed Subject	No	95	94.1
	Yes	6	5.9

Table 1 shows that the sample was evenly distributed across age groups and gender, with BSIT and BLIS programs comprising the majority of respondents. The predominance of first-year students (50.5%) reflects typical enrollment patterns in computing programs. The low percentage of students engaged in paid work (6.9%) aligns with findings by Gutiérrez-de-Rozas et al. (2022) that Philippine state university students are primarily dependent on family support rather than employment income. The low incidence of INC grades (5.0%) and course failures (5.9%) suggests either effective academic support systems or potential underreporting due to the stigma associated with academic setbacks (Namoun & Alshanqiti, 2021). While only 11 students reported actual academic setbacks, surveying the entire population of 101 students aligns with proactive Educational Data Mining (EDM) frameworks (Romero & Ventura, 2020), allowing the identification of systemic risk factors and early warning indicators across the general student body before formal setbacks occur.

Factors Contributing to Academic Setbacks

As shown in Table 2, all 15 factors fell within the moderate-to-low range. Financial Difficulties (M=3.22), Heavy Course Load (M=3.14), and Time Management Issues (M=3.10) were the top three contributors, while Lack of Prerequisite Knowledge (M=2.52) and Family Problems (M=2.57) registered as low factors. The uniformly high standard deviations (SD=1.13–1.35) indicate highly polarized perceptions, reflecting diverse socioeconomic circumstances within the CCIS student population.

Table 2. Descriptive Statistics: Factors Contributing to Academic Setbacks (N=101)

Factor	M	SD	Min	Max	Interpretation
Financial Difficulties	3.22	1.26	1.0	5.0	Moderate Factor
Heavy Course Load	3.14	1.19	1.0	5.0	Moderate Factor
Time Management Issues	3.10	1.13	1.0	5.0	Moderate Factor
Internet Connectivity Problems	3.07	1.28	1.0	5.0	Moderate Factor
Lack of Resources/Materials	3.01	1.18	1.0	5.0	Moderate Factor
Stress/Pressure	2.98	1.35	1.0	5.0	Moderate Factor
Teaching Style Mismatch	2.82	1.24	1.0	5.0	Moderate Factor
Lack of Motivation	2.78	1.18	1.0	5.0	Moderate Factor
Poor Study Habits	2.77	1.13	1.0	5.0	Moderate Factor
Procrastination	2.76	1.21	1.0	5.0	Moderate Factor
Transportation Issues	2.71	1.32	1.0	5.0	Moderate Factor
Work Commitments	2.65	1.22	1.0	5.0	Moderate Factor
Health Issues	2.61	1.28	1.0	5.0	Moderate Factor
Family Problems	2.57	1.31	1.0	5.0	Low Factor
Lack of Prerequisite Knowledge	2.52	1.18	1.0	5.0	Low Factor

Note. Scale: 1.0–1.80=Very Low; 1.81–2.60=Low; 2.61–3.40=Moderate; 3.41–4.20=High; 4.21–5.0=Very High Factor. M=Mean; SD=Standard Deviation.

Table 2 reveals that financial difficulties emerged as the primary barrier to academic success (M=3.22), consistent with Gutiérrez-de-Rozas et al. (2022) who found material resource constraints predict academic failure through multiple pathways including limited access to learning materials and technology. The clustering of heavy course load (M=3.14) and time management issues (M=3.10) as secondary factors suggests that academic demands interact with resource constraints to create compound barriers. The uniformly high standard deviations (SD=1.13–1.35) indicate highly polarized perceptions, reflecting diverse socioeconomic circumstances within the student population. This variability supports the need for differentiated rather than one-size-fits-all interventions (Albreiki et al., 2021).

Support System Utilization

Family Support (M=3.23) and Library Resources (M=3.10) were the most utilized support systems, while Academic Counseling/Advising (M=2.46) and Instructor Consultation during Office Hours (M=2.45) were the lowest rated (Table 3). The overall grand mean of M=2.81 reflects moderate aggregate utilization, masking a critical underutilization of formal institutional services—precisely those most capable of early academic intervention.

Table 3. Support System Utilization Among CCIS Students (N=101)

Support System	M	SD	Interpretation
Family Support	3.23	1.41	Moderate Utilization
Library Resources	3.10	1.20	Moderate Utilization
Online Learning Services	2.90	1.15	Moderate Utilization
Peer Tutoring/Study Groups	2.74	1.08	Moderate Utilization
Academic Counseling/Advising	2.46	1.08	Low Utilization
Instructor Consultation (Office Hours)	2.45	1.12	Low Utilization
Grand Mean	2.81	1.17	Moderate Utilization

Table 3 shows that family support (M=3.23) and library resources (M=3.10) were the most utilized support systems, while formal institutional services—academic counseling (M=2.46) and instructor consultation (M=2.45)—were markedly underutilized. This pattern aligns with Namoun and Alshanqiti's (2021) finding that students most in need of academic intervention are least likely to voluntarily seek formal support, driven by stigma, low awareness, and structural access barriers. The overall grand mean of M=2.81 masks a critical service delivery gap: students rely on informal support (family, peers) rather than professional academic services precisely when early intervention could prevent setbacks from compounding into dropout.

Emotional Impact of Academic Setbacks

Determination to Succeed (M=3.62) was the dominant emotional response, reaching the 'High Impact' threshold (Table 4). Fear of Disappointing Family (M=3.20) and Motivation to Improve (M=3.15) were also prominent. The grand mean of M=3.03 (Moderate) indicates a collectively resilient but emotionally burdened student population. The contrast between high determination and moderate stress and anxiety signals latent resilience capital that institutional support can activate.

Table 4. Emotional Impact of Academic Setbacks on CCIS Students (N=101)

Emotional Response	M	SD	Interpretation
Determination to Succeed	3.62	1.47	High Impact
Fear of Disappointing Family	3.20	1.57	Moderate Impact
Motivated to Improve	3.15	1.33	Moderate Impact
Stress/Pressure	2.98	1.35	Moderate Impact
Loss of Confidence	2.70	1.27	Moderate Impact
Anxiety about Academic Performance	2.55	1.36	Low Impact
Grand Mean	3.03	1.39	Moderate Impact

Note. Scale: 1.0–1.80=Very Low; 1.81–2.60=Low; 2.61–3.40=Moderate; 3.41–4.20=High; 4.21–5.0=Very High Impact.

Table 4 reveals that determination to succeed (M=3.62) was the dominant emotional response, reaching the 'High Impact' threshold. This finding indicates substantial resilience capital among students experiencing academic difficulties. Fear of disappointing family (M=3.20) reflects the collective orientation of Filipino student identity, where academic performance carries emotional weight beyond individual achievement (Wong et al., 2024). The contrast between high determination and moderate stress suggests that proactive advising can leverage this resilience before chronic stress erodes this protective buffer.

Correlation Analysis

Table 5 presents the top Spearman rank-order correlations (ρ). Five very strong relationships ($\rho \geq 0.922$) emerged exclusively among academic contributing factors, indicating that these stressors cluster and compound simultaneously. The Transportation Issues–Internet Connectivity correlation ($\rho=0.953$) illustrates a dual logistical-digital barrier concentrated among off-campus and commuter students. Moderate factor-to-emotion correlations ($\rho=0.411$–0.499) confirm that academic stressors directly translate into psychological distress, with Subject Difficulty–Anxiety ($\rho=0.499$) emerging as the strongest cross-domain relationship. All correlations were significant at $p<.001$.

Table 5. Spearman Correlation: Analysis Top Relationships Between Contributing Factors and Emotional Outcomes

Variable Pair	ρ	Strength	Interpretation
Transportation Issues ↔ Internet Connectivity Problems	0.953	Very Strong	Logistical & digital barriers co-occur
Poor Study Habits ↔ Lack of Prerequisite Knowledge	0.943	Very Strong	Behavioral & preparedness deficits cluster
Poor Study Habits ↔ Heavy Course Load	0.929	Very Strong	Study behavior compounds workload burden
Lack of Prerequisite Knowledge ↔ Heavy Course Load	0.927	Very Strong	Preparation gaps amplify course difficulty
Health Issues ↔ Family Problems	0.922	Very Strong	Personal stressors co-occur
Subject Difficulty ↔ Anxiety about Performance	0.499	Moderate	Academic challenge drives psychological distress
Work Commitments ↔ Loss of Confidence	0.422	Moderate	Employment conflict erodes self-efficacy
Financial Difficulties ↔ Loss of Confidence	0.413	Moderate	Resource scarcity undermines confidence
Health Issues ↔ Anxiety about Performance	0.411	Moderate	Health stressors fuel performance anxiety

Note. All correlations $p<.001$. Strength: $\rho \geq 0.80$=Very Strong; 0.60–0.79=Strong; 0.40–0.59=Moderate; 0.20–0.39=Weak.

Table 5 reveals that the strongest correlations ($\rho \geq 0.922$) occur exclusively among academic and logistical contributing factors, indicating that these stressors do not operate in isolation but rather cluster and compound simultaneously. For instance, the near-perfect correlation between Transportation Issues and Internet Connectivity

Problems (ρ = 0.953) illustrates a dual logistical-digital barrier that disproportionately affects off-campus and commuter students. Similarly, the tight clustering of Poor Study Habits, Lack of Prerequisite Knowledge, and Heavy Course Load (ρ = 0.927–0.943) suggests that behavioral deficits and academic unpreparedness amplify the burden of coursework. These structural interdependencies corroborate the findings of Albreiki et al. (2021), who noted that academic challenges in computing programs are multidimensional and require holistic interventions rather than single-issue solutions. Furthermore, the moderate cross-domain correlations (ρ = 0.411–0.499) between academic factors and emotional outcomes—particularly Subject Difficulty and Anxiety (ρ = 0.499)—confirm that academic stressors directly translate into psychological distress, supporting the integration of mental health resources within academic support frameworks (Wong et al., 2024).

Year-Level Differences (One-Way ANOVA)

ANOVA results (Table 6) revealed significant year-level differences for three factors, all with medium effect sizes (η^2=0.07–0.12). Second-year students consistently reported the highest means across Transportation Issues, Lack of Resources, and Internet Connectivity. Tukey's HSD post-hoc tests confirmed that second-year students were significantly higher than both first- and third-year peers for Transportation Issues (p=.004; p=.005), and significantly higher than third-year for Lack of Resources (p=.018). H_{01} is rejected for these three factors..

Table 6. One-Way ANOVA Results: Factors with Significant Year-Level Differences

Factor	F	p	η^2	Effect Size	M (1st/2nd/3rd)	Tukey HSD Post-Hoc Significant Pairs
Transportation Issues	6.16	.003	.12	Medium	2.40/3.34/2.38	2nd>1st (p=.004); 2nd>3rd (p=.005)
Lack of Resources/Materials	4.43	.015	.09	Medium	2.92/3.47/2.50	2nd>3rd (p=.018); 2nd>1st (p=.046)
Internet Connectivity Problems	3.61	.031	.07	Medium	2.81/3.56/3.00	2nd>1st (p=.029)

Note. η^2: 0.01=small, 0.06=medium, 0.14=large. 4th-year (n=1) excluded. Post-hoc: Tukey's HSD.

Table 6 indicates that while overall stress levels remain relatively consistent across year levels, significant differences emerge specifically in logistical and resource-based barriers, with second-year students reporting the highest levels of difficulty. Second-year students exhibited significantly higher mean scores for Transportation Issues (M = 3.34) compared to both first-year (p = .004) and third-year (p = .005) peers, as well as higher Lack of Resources (M = 3.47) compared to third-year students (p = .018). This pattern aligns with the "sophomore slump" phenomenon documented in higher education literature (Albreiki et al., 2021), where the transition from foundational to specialized computing coursework intensifies resource demands before students have fully developed effective coping strategies or established stable support networks. The medium effect sizes (η^2 = 0.07–0.12) suggest that year level is a meaningful predictor of these specific barriers, highlighting the critical need for targeted institutional interventions—such as enhanced resource allocation and proactive advising—specifically tailored to support students during their second year of study.

Employment Status and INC Experience (Chi-Square)

The chi-square test revealed no significant association between work status and incomplete grade experience ($\chi^2(1)$=0.38, p=.538; Cramer's V=0.061) (Table 7). All five incomplete grade recipients were students not engaged in paid work. Fisher's Exact Test (p=1.000), applied due to expected cell frequencies below 5 in the part-time working group, confirmed the non-significant result. H_{02} is retained; however, the small sample of working students (n=7) and incomplete grade recipients (n=5) constrains statistical power significantly.

Table 7. Chi-Square Test: Employment Status × INC Grade Experience

Employment Status	No INC n (%)	Yes INC n (%)	Total	$\chi^2(1)$	p
Not Working	89 (94.7%)	5 (5.3%)	94	0.38	.538
Working Part-time	7 (100%)	0 (0.0%)	7	—	—
Total	**96**	**5**	**101**		

Note. Cramer's V=0.061 (Very Weak). Fisher's Exact Test p=1.000
(applied due to low expected cell frequencies).

Table 7 presents the cross-tabulation and chi-square analysis examining the relationship between students' work status and their experience with incomplete grades. The analysis revealed no statistically significant association between the two variables ($\chi^2(1) = 0.38$, $p = .538$), with all five students who reported receiving an incomplete grade falling within the non-working category. However, it is crucial to interpret this finding within the context of the sample's demographic skew; only 6.9% (n = 7) of the respondents were engaged in part-time work, resulting in low expected cell frequencies that necessitated the use of Fisher's Exact Test (p = 1.000). Consequently, while the data suggests that work status is not a primary risk factor for incomplete grades in this specific cohort, the extremely small subsample of working students precludes any definitive conclusions regarding the impact of work commitments on academic completion. This finding underscores the necessity for future research to oversample working students to achieve adequate statistical power, while also indicating that in this context, academic setbacks are more likely driven by other factors such as financial difficulties or resource constraints rather than direct employment conflicts.

Predictors of Stress/Pressure (Multiple Linear Regression)

The regression model was statistically significant overall ($F(15,72)=2.82$, $p=.002$, $R^2=0.370$) and explained 37% of the variance in student stress (Table 8). Lack of Resources/Materials ($\beta=0.433$), Work Commitments ($\beta=0.320$), and Difficulty of Subject Matter ($\beta=0.303$) were the three strongest positive predictors. H_{03} is therefore rejected. The negative coefficients for Transportation Issues ($\beta=-0.299$) and Procrastination ($\beta=-0.263$) likely reflect suppressor effects in the multi-predictor model and should not be interpreted as protective factors against stress. The gap between $R^2=0.370$ and Adjusted $R^2=0.239$ indicates risk of overfitting with 15 predictors and n=88, warranting a reduced model in future replication studies.

Table 8. Multiple Linear Regression: Predicting Stress/Pressure from Contributing Factors (n=88)

Predictor	B	SE	β	p	Interpretation
Lack of Resources/Materials	0.47	0.11	0.433	.001	Strongest positive predictor of stress
Work Commitments	0.36	0.12	0.320	.004	Balancing employment drives stress
Difficulty of Subject Matter	0.31	0.11	0.303	.008	Challenging coursework elevates stress
Transportation Issues	−0.29	0.10	−0.299	.004	Suppressor effect; caution in interpretation

Procrastination	−0.27	0.11	−0.263	.014	Suppressor effect; caution in interpretation
Model Summary	R^2=0.370 | Adj. R^2=0.239 | F(15,72)=2.82, p=.002 | n=88				

Note. B=unstandardized; SE=standard error; β=standardized coefficient.
Negative β values indicate suppressor effects. Model: F(15,72)=2.82, p=.002.

Table 8 details the multiple linear regression model developed to predict students' stress and pressure levels based on 15 contributing academic and logistical factors. The model was statistically significant (F(15, 72) = 2.82, p = .002) and explained 37.0% of the variance in stress scores (R^2 = 0.370). The strongest positive predictors of stress were identified as Lack of Resources/Materials (β = 0.433, p = .001), Work Commitments (β = 0.320, p = .004), and Difficulty of Subject Matter (β = 0.303, p = .008). The prominence of resource scarcity as the primary driver of psychological distress extends the findings of Meghji et al. (2023), suggesting that material constraints in computing programs directly elevate mental health burdens, thereby positioning resource equity as both an academic and psychological intervention. While the negative coefficients for Transportation Issues and Procrastination likely reflect statistical suppressor effects within the multi-predictor model and should not be interpreted as protective factors, the overall model fit indicates that 63% of the variance in stress remains unexplained. This substantial unexplained variance highlights the critical need for future predictive models to incorporate psychosocial variables, such as academic self-efficacy, resilience, and social support quality, to provide a more comprehensive understanding of student well-being (Waheed et al., 2023).

Data Visualization Charts

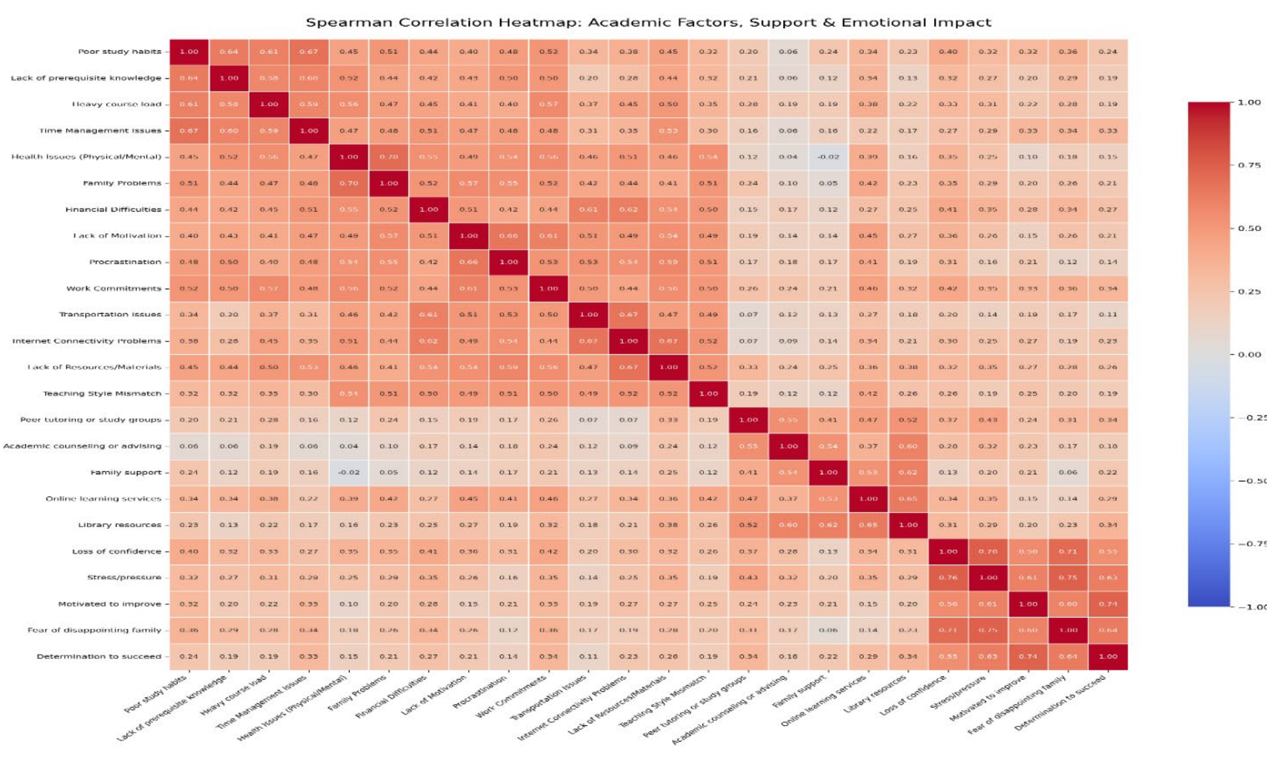

Fig. 2. Spearman Correlation Heatmap for Academic Factors, Support & Emotional Impact

The figure above shows that a Spearman rank-order correlation matrix maps the strength and direction of the relationships between academic factors, support systems, and emotional outcomes. Strong positive correlations dominated the academic domain, particularly between poor study habits and lack of prerequisite knowledge (ρ =

.943), poor study habits and heavy course load (ρ = .929), and lack of prerequisite knowledge and heavy course load (ρ = .927), suggesting that behavioural and preparatory deficits combine to create overwhelming academic burdens. Logistical barriers also showed near-perfect alignment, with transportation and Internet connectivity issues correlating at ρ = .953. On the emotional dimension, stress/pressure, loss of confidence, and fear of disappointing family formed a tightly interconnected cluster, demonstrating how academic difficulties cascade into psychological distress. Conversely, institutional support systems (e.g., peer tutoring and academic counseling) exhibited weaker correlations with these negative factors, indicating that they may function as independent buffering mechanisms rather than direct statistical counterweights to core academic struggles.

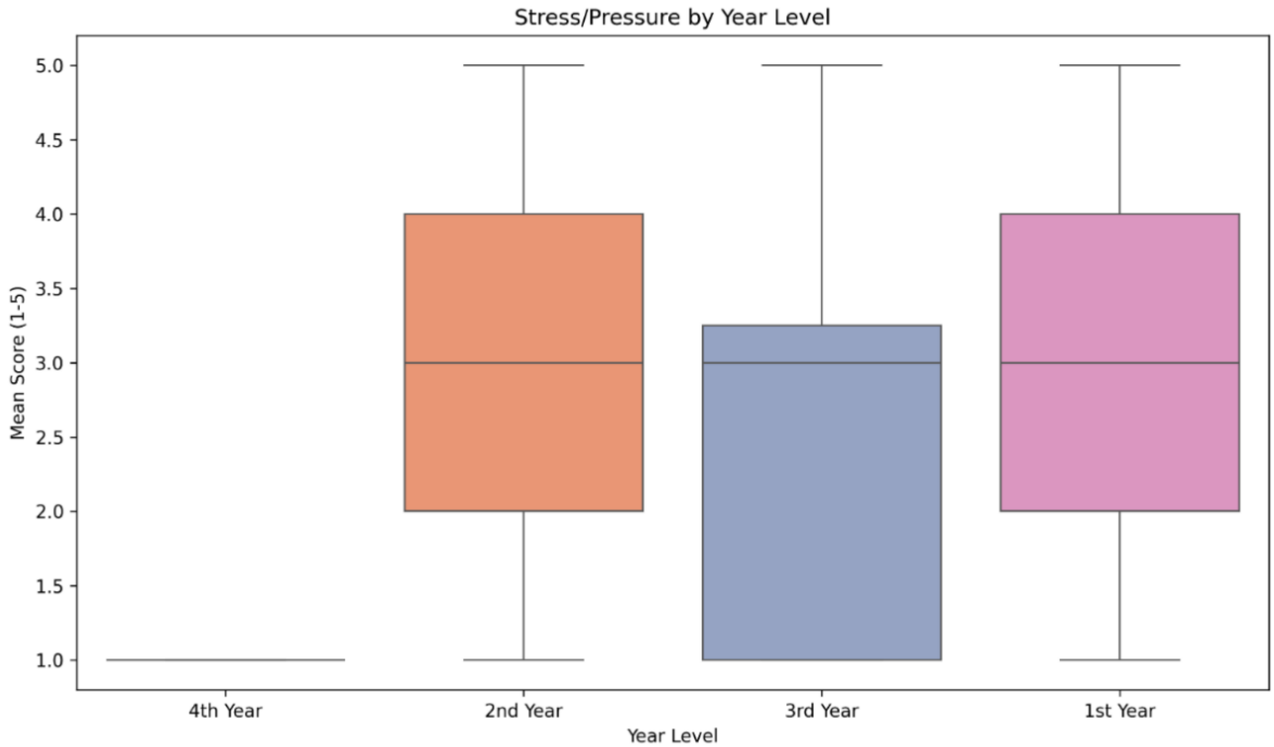

Fig. 3. ANOVA- Boxplot for Stress/Pressure by Year Level

The figure above shows that a one-way ANOVA was conducted to examine differences in stress and pressure levels across academic year levels, revealing that stress remains a consistent and moderate concern throughout the student journey ($M = 2.98$, $SD = 1.35$). Except for the fourth-year cohort ($n = 1$), first-, second, and third-year students all exhibited median scores clustered around 3.0. The second-year group displayed greater variability (interquartile range: 2.0–4.0), while third-year students showed an upper whisker extending to 5.0, suggesting that a subset of students experienced extreme stress. These visual patterns align with the non-significant ANOVA result ($p \geq .05$), positioning stress as a pervasive, year-level-agnostic factor rather than one that escalates or declines predictably with academic progression.

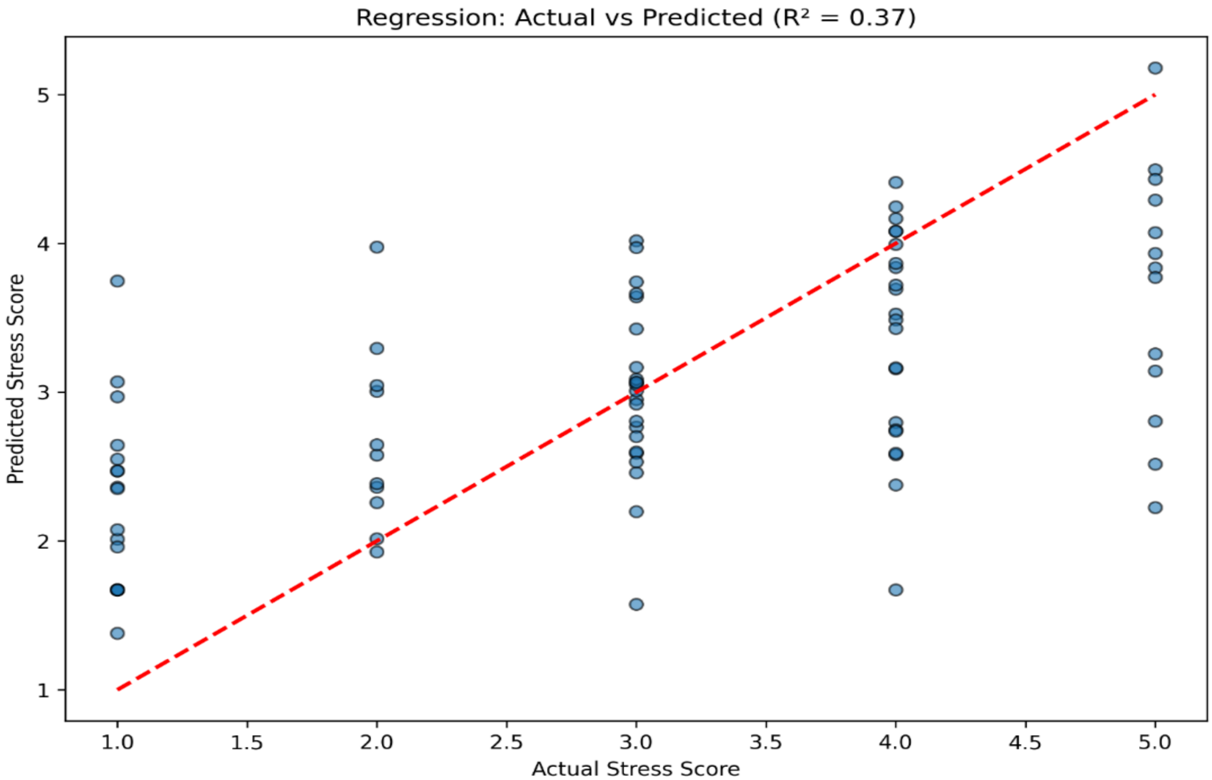

Fig. 4. Scatter Plot for Regression: Actual vs Predicted (R^2 = 0.37)

The figure above shows that a multiple linear regression model was evaluated to predict students' stress/pressure levels based on 15 contributing academic and logistical factors. The model explained 37.0% of the variance in stress scores (R^2 = .370, Adjusted R^2 = .239) based on a complete-case sample of n = 88 respondents. The red dashed line represents the line of perfect prediction, and the clustering of the data points around it demonstrates a moderate model fit. Unstandardized regression coefficients indicated that the strongest positive predictors of stress were lack of resources/materials (β = 0.433), work commitments (β = 0.320), and difficulty in the subject matter (β = 0.303). The scatter of points above and below the regression line reveals that while these academic and logistical factors are meaningful predictors, a substantial portion of the variance (63.0%) is attributable to other unmeasured variables, suggesting that targeted academic interventions may only partially mitigate students' stress.

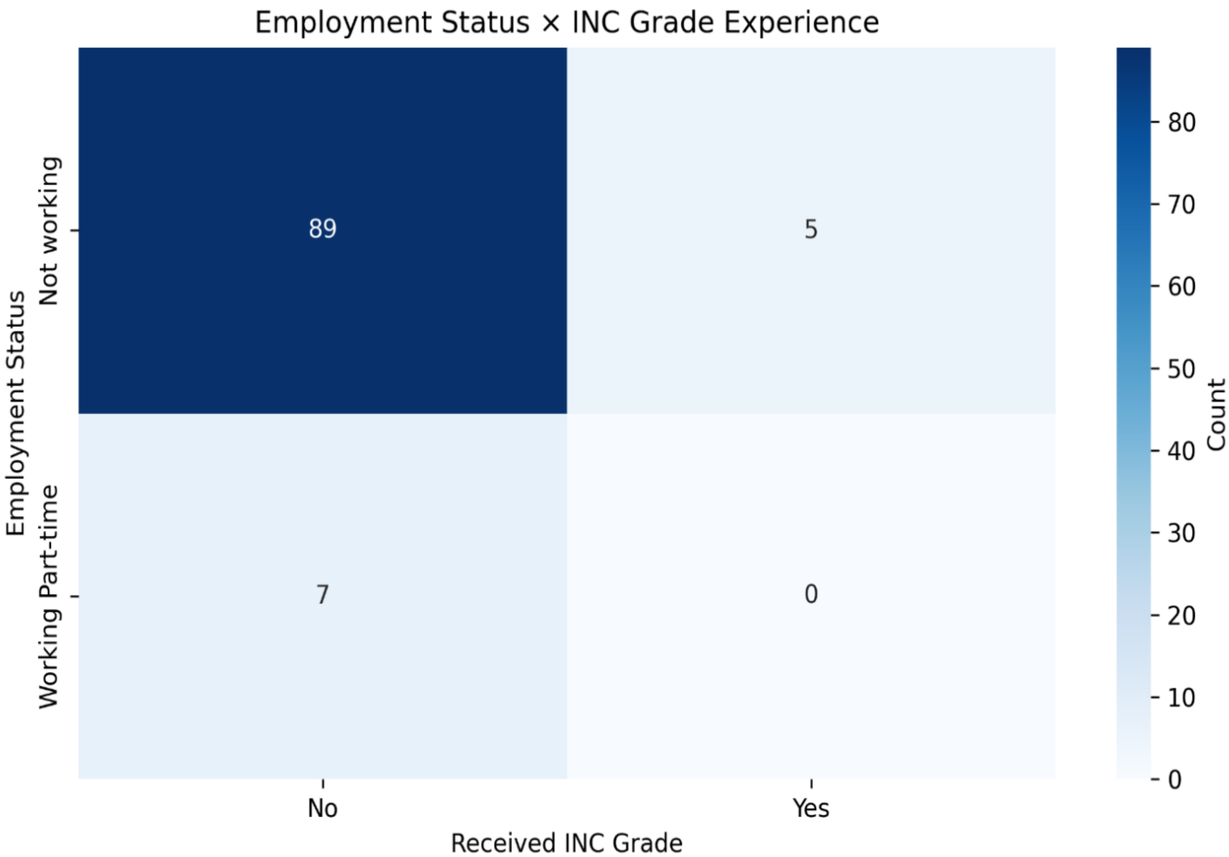

Fig. 5. Chi-Square Heatmap for Employment Status × INC Grade Experience

The figure above shows that a contingency analysis visualized the cross-tabulation between work status and experience with incomplete grades, highlighting a clear demographic skew in the sample. The vast majority of respondents (93.1%, n = 94) reported that they were not engaged in paid work, and all five students who indicated receiving an incomplete grade fell within this non-working category. Conversely, none of the seven part-time students reported an incomplete grade.

Owing to low expected cell frequencies, a formal chi-square test of independence was not computed, as such small subsamples violate the assumption of expected counts ≥ 5. Consequently, while the visual distribution might superficially suggest that part-time work does not negatively impact academic completion in this cohort, the extremely limited number of working respondents (n = 7) precludes any statistically reliable association between the two. The chart primarily underscores that, within this specific dataset, academic struggles are concentrated among non-working students, and work status should not be interpreted as a primary risk factor without a more balanced sample size.

DISCUSSION

Socioeconomic and Structural Barriers

The dominance of Financial Difficulties (M=3.22) as the primary contributor to academic setbacks corroborates international findings that material resource constraints impede academic performance through multiple pathways—limited access to learning materials, technology, and adequate study environments—rather than through a single mechanism. Gutiérrez-de-Rozas et al. (2022) established that financial difficulty predicts both academic failure and dropout intention through the erosion of academic self-efficacy, a pattern that the present study's moderate Loss of

Confidence rating (M=2.70) independently corroborates within the context of this study. The tight cluster of very strong correlations (ρ=0.922–0.953) among academic factors confirms that barriers do not operate in isolation; transportation deficits predict connectivity problems, and preparedness gaps amplify workload burden. Single-issue interventions are unlikely to be sufficient given this structural interdependence.

Second-Year Students as a Priority Cohort

The consistent elevation of second-year students' ratings across all three ANOVA-significant factors—with medium effect sizes—identifies this cohort as a critical transition point warranting targeted institutional attention. This pattern is consistent with the 'sophomore slump' documented in the computing education literature (Albreiki et al., 2021), wherein the transition from introductory to specialized coursework intensifies resource demands before students have established effective coping strategies. The post-hoc findings that second-year students significantly exceed both first- and third-year peers on transportation and resource barriers suggest that these pressures peak in the second year and partially resolve through attrition or adaptation by the third year—a pattern with serious implications for early dropout identification.

Stress Predictors and Mental Health Integration

The identification of Lack of Resources/Materials as the strongest stress predictor (β=0.433) positions resource equity as simultaneously an academic performance and a student mental health intervention. This finding extends Meghji et al.'s (2023) demonstration that resource-related barriers serve as early predictive signals of academic risk by showing that these barriers also directly elevate psychological distress—suggesting that resource investments yield dual returns on both performance and well-being. The overall model fit (R^2=0.370) leaves 63% of variance unaccounted for, pointing to the need to incorporate psychosocial variables such as academic self-efficacy, resilience, and social support quality in future predictive models (Waheed et al., 2023). Students' high Determination to Succeed (M=3.62) amid moderate stress indicates resilience capital that proactive advising can leverage before chronic stress erodes this protective buffer (Wong et al., 2024).

Underutilization of Formal Support Services

The critically low utilization of Academic Counseling (M=2.46) and Instructor Consultation (M=2.45) represents a structural service delivery gap. Namoun and Alshanqiti (2021) noted that students most in need of academic intervention are also the least likely to voluntarily seek support, driven by stigma, low awareness, and structural access barriers. This finding argues strongly against the current reactive advising model and supports embedding mandatory advising check-ins into regular curriculum activities—particularly at the onset of the second year. Family expectations (Fear of Disappointing Family, M=3.20) further underscore the importance of culturally responsive advising approaches that acknowledge the collective orientation of Filipino student identity and the emotional weight of academic setbacks within family contexts.

Limitations

Limitations include: the cross-sectional design precludes causal inference; self-reported survey data may be subject to recall and social desirability biases, as direct transcript verification was not feasible due to privacy constraints; the small number of incomplete grade recipients (n=5) and failing grades (n=6) constrains statistical power for association tests, rendering those specific findings exploratory; single-institution sampling limits generalizability; and the regression model does not include psychosocial or personality-level variables. Common method bias is a concern given single-source data collection; future studies should integrate LMS behavioral data with survey responses. Longitudinal designs tracking cohorts across multiple semesters would enable causal modeling and intervention evaluation.

CONCLUSION

This study applied descriptive, correlational, ANOVA, chi-square, and regression analyses to survey data from 101 computing students to identify the antecedents and emotional consequences of academic setbacks. Financial Difficulties, Heavy Course Load, and Time Management Issues emerged as the primary contributors to academic setbacks, while the regression model—significant at $p=.002$, $R^2=0.370$—identified Lack of Resources/Materials as the strongest predictor of student stress. Second-year students faced disproportionate resource and connectivity barriers, confirmed by post-hoc pairwise comparisons.

Despite moderate stress levels, students demonstrated high Determination to Succeed ($M=3.62$), indicating resilience capital that targeted interventions can activate. The study recommends: (1) implementing data-driven early warning systems with second-year-specific thresholds; (2) restructuring academic advising from reactive to mandatory proactive models embedded within the curriculum; (3) expanding resource equity programs—textbook lending, technology loans, and connectivity infrastructure; and (4) integrating stress management workshops into academic support services. Future research should employ longitudinal, multi-institutional designs incorporating LMS behavioral data and quasi-experimental intervention trials.

RECOMMENDATION

Institutional Support: Launch a simple early-alert system using mid-term grades, attendance, and LMS activity to spot struggling students early especially second-years. Expand financial aid (emergency funds, textbook/tech loans) and strengthen industry ties for scholarships and internships. Upgrade core resources: library materials, lab equipment, and campus Wi-Fi. Make study-skills workshops mandatory for first-years, and shift advising from reactive to proactive, with trained advisors reaching out before problems escalate. Add peer mentoring and targeted orientation to support the second-year transition, and embed mental health resources like stress-management workshops directly into academic support services.

Student Actions: Seek help early. Use advising, tutoring, or counseling at the first sign of trouble—not after grades drop. Build consistent study routines, use planning tools, and join study groups for tough courses. Talk to instructors sooner rather than later; most are willing to help if you reach out.

Future Research: Track students over time to see what interventions actually move the needle. Test specific programs (mentoring, financial literacy, study skills) with controlled designs. Use interviews or focus groups to capture student voices behind the numbers. Replicate the study across institutions to check generalizability, and apply moderation/mediation analyses to understand how factors like family support interact with financial stress. Finally, combining survey responses with LMS behavioral data could power smarter, real-time predictors of student success.

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