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ANXIETY CLOUDS THE FUTURE: ANTICIPATORY ANXIETY AND FUTURE OUTLOOK AMONG COLLEGE STUDENTS IN INDIA DURING COVID-19

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***ABSTRACT*:**

The COVID-19 pandemic created uncertainty for college students worldwide, heightening anticipatory anxiety and adversely affecting their outlook on the future. This study examined the prevalence of anticipatory anxiety and its association with future outlook among Indian college students during COVID-19, comparing Indian domestic and African international students. Data were collected via an online survey (Google Forms) using snowball sampling in March 2021. A sample of 78 students (50 Indian domestic, 28 African international) completed three validated instruments: the Generalised Anxiety Disorder-7 (GAD-7), the Penn State Worry Questionnaire (PSWQ), and the Dark Future Scale. Findings show a high prevalence of moderate-to-severe anxiety on the GAD-7 (89.7%), much higher than pre-pandemic levels. No participants met the clinical cutoff on the PSWQ, but 37.2% scored high on the Dark Future Scale, indicating elevated future anxiety. All measures correlated significantly ($r = .29$ to $.55$). Demographics (age, gender) explained little variance in future anxiety ($R^2 = .01$), but adding GAD-7 and PSWQ scores explained an additional 21% (full $R^2 = .22$, $p < .001$). Surprisingly, Indian domestic students scored higher on the GAD-7 than African international students ($p = .013$, $d = 0.60$), with no group differences on the other scales. The pandemic increased state anxiety but did not change trait worry. The Indian educational environment may be more anxiety-provoking than for international students. Targeting worry could improve future outlooks. Further research with larger, more diverse samples is needed.

Keywords: *Anticipatory Anxiety, College Students, International Students, COVID-19, GAD-7, PSWQ, Future Outlook, Haryana, India,*

INTRODUCTION

Anxiety is one of the most prevalent emotional responses to real or perceived threats and can manifest across multiple domains of functioning, including worry, avoidance behaviors, and physiological arousal (Szuhany & Simon, 2022). For college students, transitional life demands such as academic pressure, career uncertainty, and social adjustment render this population particularly susceptible to anxiety disorders. Despite the high burden of anxiety, approximately 40% of students experiencing clinically significant symptoms do not seek professional help (Tiller, 2012). Clinically, anxiety disorders are characterized by persistent, uncontrollable fear responses that last for weeks or months and often lead to defensive and avoidance behaviors. The DSM-5 and ICD-11 categorize anxiety disorders into seven primary subtypes (American Psychological Association, 2020). Anticipatory anxiety is a dimension observed across multiple anxiety disorders, including Generalized Anxiety Disorder (GAD) and Panic Disorder, and refers specifically to the fearful apprehension of uncertain future events (Grupe & Nitschke, 2013). Common triggers include high-stakes evaluations, career transitions, and interpersonal challenges; negative experiences in one domain may generalize to broader future-oriented anxiety (Wright et al., 2016). Within this context, anticipatory anxiety is the fearful apprehension of uncertain future events and has emerged as a particularly salient psychological concern. Understanding this anxiety is essential not only for addressing immediate student welfare but also for informing mental health preparedness for future crises and establishing baselines for post-pandemic recovery.

College students represent a high-risk group for anticipatory anxiety due to the convergence of academic demands, identity development, and major life transitions (Bruffaerts et al., 2018; Lederer et al., 2021). Indian college students face a particularly complex constellation of stressors. The Indian educational landscape is characterized

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by intense competition, high parental expectations, and cultural pressure to pursue prestigious careers, all of which may heighten anxiety beyond levels observed in Western contexts (Banu et al., 2015; Pandey et al., 2021). Recent cross-sectional studies document substantial anxiety prevalence; for example, Baruah and Sinha (2023) found that 42.6% of surveyed students experienced moderate-to-severe anxiety, while Singh and Agarwal (2023) reported that 38.2% of engineering students in Maharashtra met criteria for an anxiety disorder. Final-year students, in particular, report elevated anticipatory anxiety about campus placements and postgraduate transitions (Kaur et al., 2020; Venkatesh & Reddy, 2021). Academic pressures, including the need to meet high parental expectations and achieve competitive scores in high-stakes examinations, are compounded by financial insecurity and the socio-cultural weight of family honor (Srivastava & Srivastava, 2020). The prevalence of anxiety disorders among college students has increased markedly over the past decade. A meta-analysis by Li et al. (2022) estimated that approximately 31.9% of students globally exhibit clinically significant anxiety symptoms. The World Health Organization (WHO) World Mental Health Surveys found that 35% of first-year students across 19 countries met criteria for at least one common mental disorder, with anxiety being the most prevalent condition (Bruffaerts et al., 2018; Bantjes et al., 2021).

The COVID-19 pandemic created a uniquely severe context for anticipatory anxiety by simultaneously disrupting academic continuity, financial stability, social support systems, and mental health services. The abrupt shift to online learning, examination cancellations, employment uncertainty, and physical isolation coalesced to produce unprecedented psychological strain. Meta-analytic evidence indicates that anxiety prevalence among college students rose from approximately 31% pre-pandemic to 45-55% during the pandemic, with some regions reporting rates exceeding 80% (Li et al., 2022). In India, studies document a threefold increase in clinically significant anxiety symptoms during the second COVID-19 wave (Nair & Matthew, 2023). Students from rural backgrounds face additional challenges as they navigate the transition to urban educational environments. Alongside domestic students, India hosts a substantial number of international students, particularly from African nations, who encounter the dual burden of acculturative stress and pandemic-related restrictions. International students, particularly those from African nations studying in India, faced additional challenges, including travel restrictions, visa complications, and heightened concerns about family well-being in their home countries. However, the transition to online learning may have paradoxically reduced certain acculturative stressors, such as navigating in-person social norms in an unfamiliar cultural environment. These considerations informed the study's comparative analysis of Indian domestic and African international students.

Despite growing concern about student mental health in India, several gaps remain. First, few studies have examined anticipatory anxiety – the specific fear of future negative events – as distinct from general anxiety. Second, no known study has compared anticipatory anxiety between Indian domestic students and African international students in India, despite the unique stressors faced by both groups. Third, most studies have focused on academic performance as the primary outcome; few have examined how anticipatory anxiety shapes students' future outlook – their sense of hope, optimism, or fatalism about their life trajectory. This study addresses these gaps.

OBJECTIVES

To address these gaps, the present study is designed with the following objectives:

1. To examine the prevalence of anticipatory anxiety (operationalized using the GAD-7, PSWQ, and Dark Future Scale) among a Pan-India sample of college students.
2. To investigate the relationship between future outlook and anticipatory anxiety, specifically testing whether higher levels of anticipatory anxiety predict a more debilitated (i.e., pessimistic, hopeless, or fatalistic) future outlook.
3. To explore demographic variations (gender, age, race) in anticipatory anxiety and future outlook within the Indian context.
4. To compare anxiety and future between African and Indian college students
5. To examine the relationship between age and anxiety measures.
6. To determine the prevalence of severe to moderate anxiety symptoms among the sample.
7. To explore gender differences in future anxiety (Dark Future Scale)

METHODOLOGY

Research Design

This study employed a quantitative, cross-sectional survey design to examine anticipatory anxiety and its relationship to future outlook among college students in India during the COVID-19 pandemic. A cross-sectional design was appropriate given the study's descriptive and correlational objectives and the logistical constraints imposed by pandemic-related restrictions on in-person data collection.

Participants and Sampling

Participants were college students aged 18 to 35 years currently enrolled in undergraduate or postgraduate programs at recognized Indian universities. Data were collected via an online survey (Google Forms) distributed through snowball sampling, with the survey link shared across the researcher's personal and professional networks and through social media platforms including Facebook, WhatsApp, and LinkedIn. Although 200 responses were targeted, 100 individuals initiated the survey, of whom 78 provided complete and valid responses (78% completion rate) after excluding cases with more than 10% missing data on any scale ($n = 22$ excluded).

The final sample comprised 78 participants: 49 females (62.8%) and 29 males (37.2%). Racial composition included 50 Indian domestic students (64.1%) and 28 African international students (35.9%). No financial compensation was offered for participation.

Inclusion and Exclusion Criteria

Participants were required to meet the following inclusion criteria: (a) current enrolment in an undergraduate or postgraduate program at a recognized Indian university, (b) age between 18 and 35 years, and (c) willingness to provide informed consent. Individuals not currently enrolled at an Indian college or university, those above 35 years of age, and those residing outside India at the time of the survey were excluded.

Instruments

1. Generalized Anxiety Disorder Scale (GAD-7) - The GAD-7 (Spitzer et al., 2006) is a widely used 7-item self-report measure assessing the presence and severity of generalized anxiety symptoms over the preceding two weeks. Items are rated on a 4-point Likert scale ranging from 0 (not at all) to 3 (nearly every day), yielding total scores from 0 to 21. Established cutoffs classify scores as minimal (0 – 4), mild (5 – 9), moderate (10 – 14), or severe (15 – 21) anxiety. A score of 10 or above is recommended as the threshold for identifying probable GAD cases. The GAD-7 demonstrates strong psychometric properties, including good internal consistency (Cronbach's $\alpha = .78$) and convergent validity.
2. Penn State Worry Questionnaire (PSWQ) - The PSWQ by Meyer et al. (1990) is a 16-item self-report instrument measuring the tendency to engage in pathological, uncontrollable worry. Items are rated on a 5-point scale from 1 (not at all typical) to 5 (very typical), with total scores ranging from 16 to 80. Higher scores indicate greater worry severity, and a score of 45 or above is the established cutoff for clinically significant pathological worry. The PSWQ exhibits strong psychometric properties, including high internal consistency ($\alpha = .78$–$.95$) and good test-retest reliability ($r = .92$). In the present sample, internal consistency was $\alpha = .95$.
3. Dark Future Scale - The Dark Future Scale is a shortened version of the Zaleski Future Anxiety Scale (Zaleski, 1996), comprising items assessing anxiety, uncertainty, and fear regarding the future. Higher scores indicate greater future anxiety. The scale demonstrates good psychometric properties, with a Cronbach's alpha of .83. As no established clinical cutoff exists for this measure, participants scoring in the top tertile were classified as experiencing high future anxiety (Zaleski et al., 2019).

Data Collection Procedure

Data were collected between January and March 2021, during the second wave of the COVID-19 pandemic in India, a period marked by record-high infection rates and stringent lockdown measures. The online survey format required no in-person contact. Before proceeding, all participants were required to read and acknowledge an informed consent statement outlining the study's purpose, voluntary nature, anonymity provisions, and their right to withdraw at any time without penalty. No identifying information was collected. The survey required approximately 15–20 minutes to complete.

Snowball sampling was employed to reach geographically dispersed student populations under pandemic-related mobility restrictions (Parker et al., 2019). The study protocol was approved by the researcher's thesis supervisor and adhered to the ethical guidelines of NIMS University and the American Psychological Association. Given the sensitive nature of the anxiety assessments, a debriefing statement with mental health support resources was included at the conclusion of the survey.

Ethical Considerations

Formal ethics committee approval was not required for this study because it involved an anonymous, voluntary online survey of adult college students on non-clinical topics, with no collection of personal identifiers and minimal risk to participants. This exemption is consistent with the Indian Council of Medical Research (ICMR) National Ethical Guidelines (2017) for minimal-risk research. All participants provided informed consent prior to participation, were informed of their right to withdraw at any time, and were assured of anonymity and confidentiality. The study adhered to the principles of the Declaration of Helsinki.

Data Analysis Plan

Data were analyzed using IBM SPSS Statistics, Version 27. The following analytical procedures were performed sequentially:

1. Data screening: Missing data were examined, and cases with more than 10% missing data on any scale were excluded ($n = 22$). Little's MCAR test was conducted to verify that the remaining missing data were missing completely at random.
2. Descriptive statistics: Means, standard deviations, and frequency distributions were calculated for all study variables and demographic characteristics.
3. Reliability analysis: Internal consistency (Cronbach's α) was computed for each scale.
4. Bivariate correlations: Pearson product-moment correlations were computed to examine relationships among GAD-7, PSWQ, and Dark Future Scale scores.
5. Group comparisons: Independent-samples t-tests were used to examine differences in anxiety and future outlook across gender and racial groups.
6. Hierarchical regression: A two-block hierarchical multiple regression was conducted to test whether anxiety measures (GAD-7, PSWQ) significantly predicted Dark Future Scale scores after controlling for demographic variables (age, gender). Block 1 entered demographic covariates; Block 2 added the anxiety measures.

Statistical significance was set at $\alpha = .05$ (two-tailed). Effect sizes (Cohen's d for t-tests, η^2 for ANOVAs, and R^2 for regression analyses) are reported throughout.

RESULTS

The results are presented in the order of the research objectives and hypotheses. All findings should be interpreted in the context of data collection during the second wave of the COVID-19 pandemic in India, a period of heightened and acute stress for college students (Li et al., 2022; Nair & Matthew, 2023), and the reported prevalence rates should not be assumed to reflect typical non-pandemic conditions.

Sample Description

A total of 100 individuals initiated the online survey, of whom 78 provided complete, valid responses (completion rate = 78%). The sample comprised 49 female participants (62.8%) and 29 male participants (37.2%). With respect to racial composition, 50 participants identified as Indian (64.1%) and 28 as African (35.9%). Demographic characteristics are summarized in Tables 1 and 2.

Table 1

Demographic Characteristics of Participants by Gender ($N = 78$)

Table 2

Demographic Characteristics of Participants by Race ($N = 78$)

Objective 1: Prevalence of Anticipatory Anxiety

Table 3 presents descriptive statistics for the three anxiety measures. The mean GAD-7 score was 13.67 ($SD = 4.19$), placing the average participant in the moderate anxiety range. The mean PSWQ score was 23.17 ($SD = 3.10$), well below the clinical cut-off of 45, indicating that the sample, on average, did not meet criteria for pathological worry. The mean Dark Future Scale score was 19.73 ($SD = 7.22$), reflecting a moderately elevated orientation toward future anxiety.

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Table 3
Descriptive Statistics for Anticipatory Anxiety Measures (N = 78)

Objective 2: Bivariate Relationships Among Anxiety Measures and Future Outlook
Pearson correlations among the three measures are presented in Table 4. GAD-7 scores were moderately and positively correlated with Dark Future Scale scores (r = .46, p < .01), indicating that higher generalized anxiety was associated with a more pessimistic future outlook. PSWQ scores showed a moderate-to-strong positive correlation with Dark Future Scale scores (r = .55, p < .01), suggesting that pathological worry was even more closely linked to future anxiety than was generalized anxiety. GAD-7 and PSWQ scores were themselves significantly but weakly correlated (r = .29, p = .010), indicating that while related, they capture partially distinct aspects of anxious responding.

Table 4
Pearson Correlations Among Anticipatory Anxiety Measures (N = 78)

Objective 3: Gender Differences in Anticipatory Anxiety and Future Outlook
Independent-samples t-tests were conducted to examine gender differences across all three anxiety measures. Results are presented in Tables 5 and 6. Female participants (M = 13.71, SD = 4.15) and male participants (M = 13.62, SD = 4.32) reported nearly equivalent GAD-7 scores; the difference was not statistically significant ($t(76) = 0.09, p = .925$, Cohen's d = 0.09). Similarly, female participants (M = 20.1, SD = 7.58) and male participants (M = 18.9, SD = 6.63) did not differ significantly on the Dark Future Scale ($t(76) = 0.72, p = .475$, Cohen's d = 0.17). No significant gender differences were observed on the PSWQ.

Table 5
Group Statistics: Gender Differences in Anticipatory Anxiety (N = 78)
Objective 4: Racial Differences in Anticipatory Anxiety and Future Outlook
An independent-samples t-test was conducted to compare GAD-7, PSWQ, and Dark Future Scale scores between Indian domestic students (n = 50) and African international students (n = 28). Results are presented in Table 6. Indian students (M = 14.3, SD = 4.75) reported significantly higher GAD-7 scores than African students (M = 12.6, SD = 2.72); $t(76) = 2.56$, p = .013, Cohen's d = 0.60 (medium effect). No significant differences were observed on the PSWQ ($p = .71$) or the Dark Future Scale ($p = .08$), although the latter comparison approached significance with a medium effect size (Cohen's d = 0.42), suggesting a trend toward higher future anxiety among Indian students.

Table 6
Group Statistics and T-Test Results: Racial Differences in Anticipatory Anxiety (N = 78)

Objective 5: Age and Anxiety Measures
Pearson correlations between age and each anxiety measure are presented in Table 7. No significant relationship was found between age and GAD-7 scores ($r = -.21, p = .063$), PSWQ scores ($r = .04, p = .750$), or Dark Future Scale scores ($r = -.07, p = .530$). These findings suggest that anxiety levels did not vary systematically with age within this sample.

Table 7
Correlations Between Age and Anxiety Measures (N = 78)

Objective 6: Prevalence of Moderate-to-Severe Anxiety
Using the GAD-7 classification cutoffs established by Spitzer et al. (2006), no participant fell in the minimal anxiety category (score 0–4). A total of 8 participants (10.3%) reported mild anxiety (scores 5 – 9), 46 (59.0%) reported moderate anxiety (scores 10 – 14), and 24 (30.8%) reported severe anxiety (scores 15 – 21). Collectively, 70 participants (89.7%) scored at or above the clinical threshold of 10. These GAD-7 distributions are presented by racial group in Table 8.

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Table 8
GAD-7 Severity Distribution by Race (N = 78)

HYPOTHESIS TESTING

Hypothesis 1: Prevalence of Clinically Significant Anticipatory Anxiety

Hypothesis 1 predicted that a substantial proportion of students would report clinically significant anticipatory anxiety. This hypothesis received mixed support across the three measures. On the GAD-7, 89.7% of participants (n = 70) exceeded the clinical threshold of 10, indicating moderate-to-severe anxiety. This rate substantially exceeded pre-pandemic estimates of 31–42.6% reported in Indian college samples (Baruah & Sinha, 2023; Li et al., 2022). On the PSWQ, no participant (0%) met the clinical cutoff of 45 for pathological worry. On the Dark Future Scale, using the top percentile criterion (≥22), 29 participants (37.2%) were classified as having high future anxiety. Hypothesis 1 is therefore partially supported: clinically significant anticipatory anxiety was prevalent on the GAD-7 and, to a moderate extent, on the Dark Future Scale, but pathological worry as measured by the PSWQ was absent in this sample.

Hypothesis 2: Bivariate Associations Between Anxiety and Future Outlook

Hypothesis 2 predicted that GAD-7 and PSWQ scores would be significantly and positively associated with Dark Future Scale scores. Both relationships were statistically significant: GAD-7 and Dark Future scores were moderately correlated ($r = .46, p < .01$), and PSWQ and Dark Future scores were more strongly correlated ($r = .55, p < .01$). Hypothesis 2 is fully supported. The stronger association between PSWQ and Dark Future scores relative to GAD-7 and Dark Future scores suggests that trait worry may be a more proximal risk factor for a debilitating future outlook than state anxiety symptoms.

Hypothesis 3: Hierarchical Regression Analysis

Hierarchical multiple regression was conducted to test whether GAD-7 and PSWQ scores predicted Dark Future Scale scores beyond the variance accounted for by demographic variables. Results of both regression models are presented in Tables 9 and 10.

Table 9: Hierarchical Multiple Regression Predicting Dark Future Scale Scores: Model Summary (N = 78)

Model	R	R^2	Adjusted R^2	ΔR^2	F for ΔR^2	p for ΔR^2
1 (Age, Gender)	.10	.010	−.017	.010	.371	.691
2 (+ GAD-7, PSWQ)	.47	.220	.180	.210	9.84	< .001

Note. ΔR^2 = change in R-squared. Model 1 predictors: age, gender. Model 2 predictors: age, gender, GAD-7, PSWQ.

Table 10: Hierarchical Multiple Regression Predicting Dark Future Scale Scores: Coefficients (N = 78)

Predictor	B	SE B	β	t	p
Model 1					
Age	−.22	.38	−.08	−.58	.565
Gender (female)	1.12	1.78	.08	.63	.531
Model 2					
Age	−.20	.36	−.07	−.55	.582
Gender (female)	.99	1.68	.07	.59	.557
GAD-7	.82	.18	.48	4.52	< .001
PSWQ	.07	.24	.04	.29	.773

Note. B = unstandardized regression coefficient; SE B = standard error of B; β = standardized regression coefficient. Gender coded: 0 = male, 1 = female.

In Model 1, demographic variables (age and gender) accounted for only 1% of the variance in Dark Future Scale scores and were not statistically significant ($F(2, 75) = 0.37, p = .691$). Adding GAD-7 and PSWQ scores in Model 2 produced a significant improvement in model fit ($\Delta R^2 = .21, F(2, 73) = 9.84, p < .001$). The full model explained 22% of the variance in future anxiety ($R^2 = .22, adjusted\ R^2 = .18$). In the final model, GAD-7 was a statistically significant predictor of Dark Future Scale scores ($\beta = .48, p < .001$), whereas PSWQ approached but did not reach significance ($\beta = .04, p = .773$). Hypothesis 3 is supported.

Hypothesis 4: Comparison Between Indian and African Students
Hypothesis 4 predicted that African international students would report higher anticipatory anxiety than Indian domestic students. This hypothesis was not supported. As reported under Objective 4 (Table 6), Indian students reported significantly higher GAD-7 scores ($p = .013$, Cohen's d = 0.60, medium effect), a trend toward higher Dark Future Scale scores ($p = .08$, Cohen's d = 0.42, medium effect), and equivalent PSWQ scores ($p = .710$, Cohen's d = 0.09, negligible effect). The pattern of results directly contradicts Hypothesis 4, with Indian domestic students, not African international students, reporting higher anxiety on two of three measures.

Table 11: Summary of Hypothesis Testing Results

Hypothesis	Prediction	Finding	Supported?
H1	High prevalence of clinically significant anticipatory anxiety	89.7% (GAD-7); 37.2% (Dark Future); 0% (PSWQ)	Partial
H2	Positive correlations between anxiety and future outlook	r = .46 (GAD-7); r = .55 (PSWQ); all p < .01	Yes
H3	Anxiety measures predict future outlook beyond demographics	$\Delta R^2 = .21$, $p < .001$; full model $R^2 = .22$	Yes
H4	African students report higher anxiety than Indian students	Indian students higher on GAD-7 (p = .013) and trend on Dark Future	No

DISCUSSION

This study examined anticipatory anxiety and its relationship with future outlook among 78 college students in India during the COVID-19 pandemic. Using three validated measures—the GAD-7, PSWQ, and Dark Future Scale—alongside a comparative analysis of Indian domestic and African international students, the study aimed to address significant gaps in the existing literature. The discussion is organized around the four research hypotheses, followed by a broader consideration of clinical and educational implications.

Sample Characteristics
The sample of 78 participants showed a gender distribution consistent with trends in mental health research: 62.8% female and 37.2% male. This proportion mirrors findings from comparable studies, including Mason et al.'s (2026) study, which reported 57.9% female representation in a large first-year student sample, and Flemmer et al.'s (2025) study, which reported 68% female representation among undergraduate participants. The overrepresentation of female students may partly reflect greater willingness among women to engage in mental health research (Suresh & Dar, 2025). However, it also aligns with broader trends in higher education enrollment, where female students now constitute the majority of enrolled undergraduates in many countries.

The inclusion of 28 African international students (35.9%) alongside 50 Indian domestic students (64.1%) represents a distinctive feature of this study. Most prior research on anticipatory anxiety in Indian higher education has focused exclusively on domestic students (Baruah & Sinha, 2023; Venkatesh & Reddy, 2021), making the comparative data generated here a meaningful contribution to the literature. The high survey completion rate of 78%, substantially exceeding the typical online student survey response rate of approximately 20.9% reported in the World Mental Health International College Student Initiative (Mason et al., 2026), may reflect the salience of pandemic-related mental health concerns among participants and the facilitative role of snowball sampling in creating peer motivation to participate.

Hypothesis 1: Prevalence of Clinically Significant Anticipatory Anxiety
Hypothesis 1 received mixed support across the three measures, revealing a striking and theoretically important pattern of divergence.

GAD-7: Alarmingly High Prevalence
The finding that 89.7% of participants scored at or above the GAD-7 clinical threshold of 10 represents one of the highest prevalence rates documented in any student sample. This exceeds pre-pandemic Indian estimates of 38.2%- 42.6% (Baruah & Sinha, 2023; Singh & Agarwal, 2023) and significantly surpasses global pandemic-period estimates of 45%–55% (Li et al., 2022). Several factors plausibly account for this extreme prevalence. First, data were collected during India's second COVID-19 wave, one of the most severe and socially disruptive periods of the pandemic, characterized by a collapse of the healthcare system, high mortality, and stringent

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lockdowns. Second, the use of snowball sampling may have introduced selection bias, as students experiencing high anxiety may have been disproportionately motivated to participate. Third, the student population in India faces structural stressors, including high-stakes national entrance examinations and intense competition for limited university places, that may already elevate baseline anxiety before pandemic effects are superimposed.

Despite these considerations, the finding that nearly nine in ten participants reported moderate-to-severe anxiety is clinically significant and warrants urgent attention from university administrators and policymakers. A national survey by the Indian Ministry of Education in 2022 found that over half of college students perceived a need for mental health support. Yet fewer than 10% had received any formal help, underscoring the extent of unmet need.

PSWQ: Absence of Pathological Worry

In stark contrast to the GAD-7 findings, no participant exceeded the PSWQ clinical cutoff of 45 for pathological worry. This discrepancy is theoretically significant. The GAD-7 assesses acute anxiety symptoms over the past two weeks, capturing state anxiety responses to current environmental stressors. The PSWQ, by contrast, measures a chronic, trait-like tendency to worry excessively across contexts, a disposition that is more stable over time and less sensitive to situational fluctuations (Meyer et al., 1990). The pandemic likely elevated state anxiety without fundamentally restructuring the underlying dispositional tendency to worry. As Beiter (2021) and Hjemdal et al. (2021) suggest, situational crises produce acute anxiety responses that may subside as the crisis abates, even in the absence of changes to trait worry.

Cultural factors may also contribute to this pattern. In collectivist contexts, psychological distress is more often expressed through somatic and affective symptoms (as captured by the GAD-7) than through the cognitive rumination and generalized apprehension assessed by the PSWQ, which was developed and validated primarily in Western samples (Srivastava & Srivastava, 2020; Meyer et al. 1990). Additionally, the pervasive nature of pandemic-related worry may have led participants to perceive their anxious cognitions as entirely normative, reducing endorsement of items indicating excessive or uncontrollable worry (Nair & Matthew, 2023).

Dark Future Scale: Moderate Future Anxiety

On the Dark Future Scale, 37.2% of participants were classified as having high future anxiety—an intermediate prevalence between the very high GAD-7 rate and the zero PSWQ rate. This finding is broadly consistent with estimates from[13], who reported that approximately 47.1% of Indian college students experienced anticipatory anxiety about academic and career futures. The moderate prevalence of future-specific anxiety, in the context of very high generalized anxiety, supports theoretical distinctions between state anxiety, trait worry, and future-specific anxiety (Grupe & Nitschke, 2013) and underscores the value of measuring these dimensions separately rather than relying on any single instrument.

Hypothesis 2: Bivariate Associations Between Anxiety and Future Outlook

Hypothesis 2 was fully supported: both anxiety measures were significantly and positively correlated with Dark Future Scale scores, and all correlations were in the expected direction. The correlation between PSWQ and Dark Future scores ($r = .55$) was notably stronger than that between GAD-7 and Dark Future scores ($r = .46$), suggesting that pathological worry is more closely aligned with future-oriented anxiety than with acute anxiety symptoms. This finding is theoretically coherent: the PSWQ measures worry about anticipated events, which conceptually overlaps more directly with future anxiety than does the somatic and acute-symptom focus of the GAD-7.

These correlation magnitudes are consistent with the existing literature of Venkatesh and Reddy (2021) reported GAD–future anxiety correlations of r = .43 in Indian students; Sobol-Kwapinska (2018) reported correlations ranging from r = .41 to .48 in European young adults; and Krings (2023) found correlations between r = .44 and .52. The shared variance between GAD-7 and Dark Future scores ($r^2 = .21$) and between PSWQ and Dark Future scores ($r^2 = .30$) indicates that while these constructs are meaningfully related, they remain empirically distinct and should not be conflated in research or clinical practice.

The GAD-7 and PSWQ were themselves significantly but weakly correlated (r = .29), which is lower than meta-analytic estimates in Western clinical and student samples, which typically report r = .50–.70 (Beiter, 2021; Hjemdal et al., 2021). This weaker relationship likely reflects the state–trait distinction discussed above: during a period of acute situational anxiety, the GAD-7 captures elevated distress that does not necessarily reflect the chronic dispositional worry assessed by the PSWQ.

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Hypothesis 3: Hierarchical Regression Analysis

Hypothesis 3 was supported. The hierarchical regression demonstrated that demographic variables (age and gender) explained only 1% of the variance in future anxiety and were not significant predictors, while the addition of GAD-7 and PSWQ scores produced a significant improvement in model fit ($\Delta R^2 = .21$), with the full model explaining 22% of the variance in Dark Future Scale scores. This finding has important practical implications: it suggests that anxiety and worry levels are far more informative than demographic characteristics in identifying students at risk for a debilitating future outlook. Universal screening using the GAD-7 and PSWQ, rather than targeted screening based on demographic profiles, may therefore be the more efficient and equitable approach.

The non-significant contribution of demographic variables, particularly gender, requires comment. While prior research reports higher future anxiety in female students (Baruah & Sinha, 2023; Paul & Bhardwaj, 2022), others find no significant gender differences (Venkatesh & Reddy, 2021; Krings et al., 2023). The absence of gender effects in the present study may reflect several factors: the pandemic may have functioned as a universal stressor that overwhelmed gender-specific vulnerabilities, elevating anxiety across all students regardless of gender (Nair & Matthew, 2023); the sample size (N = 78) may have been insufficient to detect small gender effects; or the specific cultural and academic context of Indian higher education may produce anxiety profiles that are more strongly shaped by academic pressures than by gender.

The finding that the full model explained 22% of the variance in future anxiety, comparable to Sobol-Kwapinska et al. (2018), $R^2 = .19$, leaves 78% of the variance unexplained. This residual variance is attributable to factors not measured in the present study, including personality traits (neuroticism, resilience, optimism), environmental stressors (financial hardship, family dynamics), cognitive vulnerability factors (intolerance of uncertainty, catastrophizing, rumination), pandemic-specific variables (COVID-19 exposure, vaccination status), and cultural factors (collectivism, Izzat expectations). Future research should incorporate these additional predictors.

Hypothesis 4: Indian Versus African International Students

Hypothesis 4 was not supported: African international students did not report higher anticipatory anxiety than Indian domestic students. On the contrary, Indian students reported significantly higher GAD-7 scores (p = .013, Cohen's d = 0.60) and a trend toward higher Dark Future scores (p = .08, Cohen's d = 0.42), while PSWQ scores were equivalent between groups. This finding directly contradicts the assumption that the additional acculturative stressors faced by international students would produce higher anxiety relative to domestic students.

Several explanations are plausible. First, Indian higher education is characterized by extraordinarily intense academic competition, including high-stakes national examinations (e.g., JEE, NEET, CAT) with very limited acceptance rates, creating chronic anxiety from early adolescence onward (Deb et al., 2015; Kumar & Mohan, 2021). Second, the cultural concept of Izzat means that academic failure carries social consequences extending to one's family and community, amplifying the subjective stakes of academic performance in ways that may not apply equally to international students pursuing degrees abroad (Srivastava & Srivastava, 2020; Rao et al., 2022). Third, African students who successfully secured enrollment at Indian universities likely represent a positively selected subgroup characterized by above-average resilience, motivation, and institutional support—factors that may buffer against anxiety (Mori, 2000; Pedrelli et al., 2015). Fourth, the transition to online learning during the pandemic may have paradoxically reduced certain acculturative stressors for international students, such as managing in-person social interactions in a culturally unfamiliar environment, while intensifying the domestic academic pressures experienced by Indian students.

These findings carry important clinical implications. Mental health services at Indian universities should not assume that international students are the highest-risk group or that domestic students are adequately managing. Both groups require accessible, culturally sensitive mental health support. The particular pressures experienced by Indian domestic students included academic competition, examination anxiety, and family expectations, which should be explicitly addressed in institutional mental health programming.

STRENGTH AND LIMITATIONS

Several methodological limitations should be acknowledged. First, the sample size of 78 participants limits statistical power and the generalizability of findings. In particular, the non-significant trend observed for the Dark Future Scale comparison between Indian and African students ($p = .08, d = 0.42$) may reflect a genuine effect

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that the study was underpowered to detect. Second, snowball sampling likely introduced selection biases that are difficult to quantify; students with elevated anxiety may have been more inclined to participate, inflating prevalence estimates. Third, data collection during the acute second COVID-19 wave in India means that the findings reflect an extreme, time-limited stressor context and may not generalize to non-pandemic or post-pandemic periods. Fourth, the study relies entirely on self-report measures, which are subject to response biases, including social desirability and retrospective distortion. Fifth, the PSWQ was developed and validated primarily in Western contexts, and its clinical cut-off may not translate directly to Indian or African student populations. Sixth, the cross-sectional design precludes causal inference about the direction of relationships between anxiety and future outlook.

Implications for Practice and Policy

Despite these limitations, the findings have several important implications. First, the very high prevalence of moderate-to-severe anxiety on the GAD-7 (89.7%) represents a significant public health concern that requires immediate institutional response. Universities and colleges across India should implement systematic mental health screening and provide accessible, evidence-based support services. Second, the stronger association between PSWQ scores and future outlook ($r = .55$) than between GAD-7 scores and future outlook ($r = .46$) suggests that interventions specifically targeting worry cognitions, such as cognitive-behavioral therapy incorporating worry modulation, metacognitive therapy, or acceptance-based approaches, may be particularly effective in improving students' future outlook. General anxiety reduction strategies, while valuable, may be insufficient for students whose future outlook has been eroded by chronic worry. Third, future-specific interventions, including hope therapy, future-oriented coping skills training, and career construction counseling, may be warranted for the 37.2% of students who exhibited high future anxiety. Fourth, the finding that anxiety measures outperformed demographic variables in predicting future outlook supports the use of brief universal screening tools (GAD-7, PSWQ) rather than demographic targeting to identify students at risk.

Directions for Future Research

Future research should seek to replicate these findings in larger, more diverse samples encompassing multiple institutions and regions of India. Longitudinal designs would enable examination of whether pandemic-elevated anxiety persists, abates, or converts into chronic worry patterns in the post-pandemic period. Studies should incorporate additional predictors of future outlook, including intolerance of uncertainty, resilience, family expectations, and financial stressors. Culturally adapted norms and clinically relevant cut-offs for the PSWQ and Dark Future Scale should be established for Indian and African student populations. Finally, intervention research is needed to evaluate the efficacy of worry-focused and future-oriented psychological treatments for students with elevated anticipatory anxiety in Indian higher education contexts.

CONCLUSION

This study sheds light on anticipatory anxiety among Indian college students during COVID-19. Using three validated measures for 78 students, it found high state anxiety (89.7% on GAD-7), no clinically significant trait worry (0% on PSWQ), and moderate future anxiety (37.2%). This indicates the pandemic increased acute anxiety but did not change chronic worry, with implications for theory and treatment. Anxiety measures were positively linked to future outlook, with worry showing a stronger link than generalized anxiety. Regression analysis showed GAD-7 and PSWQ explained 21% of future anxiety variance beyond demographics, with the full model explaining 22%, consistent with international data. Surprisingly, Indian students reported higher generalized anxiety than African international students, likely due to the Indian educational system, intense academic competition, exams, and family expectations, creating chronic vulnerability. These findings reveal a mental health crisis needing coordinated efforts from educators, policymakers, and health professionals. Interventions should focus on worry management, screening, and addressing academic pressures. Continuous mental health monitoring and culturally adapted tools are crucial to support Indian students in fostering positive outlooks and notes toward their futures.

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