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Research Article

Student Mental Health Screening: A Multidimensional, Digital Approach for Facilitating Early Intervention

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Abstract

Background: Traditional mental health screening in university settings often relies on single-domain tools focused primarily on diagnosing mental disorders or measuring stress. Such approaches may overlook early subclinical signs of psychological distress, risk factors, and functional impairments that are crucial for timely intervention.

Objective: This study evaluates a multidimensional, digital screening framework designed to detect early mental health concerns among university students in Mumbai.

Method: A cross-sectional digital survey was administered to 442 engineering students using the Mental Health Assessment Scales for Students (MASS) battery. This comprehensive tool includes six validated instruments assessing perceived stress, psychiatric symptoms, environmental risk and vulnerability, resilience, and daily functioning. An algorithm-based digital triage system classified students into categories for self-development, counseling, or psychiatric referral.

Results: The multidimensional screening revealed that 76% of participants reported stress, with 14.3% experiencing severe stress. Notably, 21.1% exhibited clinically significant psychiatric symptoms—such as suicidal ideation, perceptual disturbances, and functional impairment—that were not identified through stress measures alone. Overall, 39.2% showed psychiatric symptoms, 31% demonstrated low resilience, and 36.6% experienced functional impairment. Significant correlations were observed among stress, psychiatric symptoms, resilience, and functioning ($p < 0.001$), highlighting the interrelated nature of these domains.

Conclusions: Findings indicate that single-domain screening tools substantially underestimate mental health risk among students. A multidimensional, symptom-centric digital screening approach provides a more accurate and early identification of at-risk individuals. Integrating such models into university mental health frameworks can enable timely, scalable, and context-sensitive interventions, ultimately improving student well-being.

Keywords

Mental Health, Multidimensional, Psychological distress.

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Introduction

Mental health problems among adolescents and young adults are a growing global concern, with higher education institutions reporting increasing prevalence of stress, anxiety, depression, and other psychological symptoms among students [1,2]. While awareness campaigns, and campus-based support programs have gained traction, a significant gap remains in the early identification and intervention of emerging mental health symptoms. One of the fundamental barriers to effective early intervention lies not only in social stigma, lack of resources, or inadequate literacy, but in a deeply embedded **clinical limitation**—the reliance on **diagnosable mental disorders** as the starting point for mental health care.

Traditionally, clinical systems have focused on identifying mental disorders based on categorical criteria (e.g., DSM-5 or ICD-11) [3,4]. However, by the time individuals meet the full diagnostic criteria, they may have already experienced prolonged psychological distress, social dysfunction, academic decline, or impaired quality of life. This delay in care is particularly concerning for student populations, where subtle or subclinical symptoms may go unnoticed or unaddressed until they escalate into psychiatric disorders [5]. The lag between symptom onset and diagnosis underscores the urgent need for a **paradigm shift toward symptom-centric identification and multidimensional screening [6].**

This paper argues that one of the most significant yet underappreciated barriers to early intervention in student mental health is the **overreliance on diagnostic thresholds for initiating care**. It proposes that early intervention efforts in university settings must **prioritize the identification of distressing or functionally impairing symptoms**, rather than waiting for diagnosable conditions to emerge. Given the lack of trained clinicians and systemic limitations, a feasible and scalable solution is to deploy **digital, multidimensional, symptom-based screening tools** capable of identifying early psychopathology across domains of mood, cognition, behavior, functioning, and interpersonal traits. A more effective approach would be to detect and monitor **psychiatric symptoms and clusters** even when they do not meet diagnostic criteria [7]. While not all symptoms necessitate clinical intervention, many subthreshold symptoms—particularly in youth—signal increased risk for progression to full-blown psychiatric disorders, including mood disorders, psychosis, schizophrenia spectrum disorders, and personality pathology [8].

Hypothesis: A multidimensional, symptom-centric digital screening approach can detect clinically meaningful psychiatric symptoms in students at an early stage—before diagnostic thresholds are reached—and facilitate timely, scalable early intervention in academic settings.

Review of Literature

Limitations of Diagnosis-Based Mental Health Systems

Traditional psychiatric services have largely been organized around diagnosing and treating mental disorders. However, diagnostic frameworks are threshold-based and exclude a large proportion of individuals with significant subclinical symptoms. Kessler et al. (2005) showed that most mental disorders begin during adolescence or young adulthood, often preceded by years of undetected or untreated symptoms. These early signs—such as sleep disturbance, irritability, anhedonia, or concentration issues—can cause substantial impairment but are frequently dismissed or normalized in academic contexts.

Moreover, there is growing recognition that categorical diagnosis may not align with the continuum of mental health experiences. Dimensional models, such as those proposed by the NIMH's Research Domain Criteria (RDoC), advocate for identifying dysfunction in specific domains rather than waiting for full disorder development [9].

Importance of Symptom Clusters in Early Detection

Studies on high-risk youth have identified specific symptom clusters—attenuated psychotic symptoms, mood instability, interpersonal difficulties, and cognitive disorganization—that frequently precede the onset of major psychiatric disorders [10]. Particularly in first-episode psychosis, mood disorders, and emerging personality disorders, early symptoms may be subtle but carry significant predictive value. The presence of such clusters can impair functioning, academic performance, and quality of life, even in the absence of a formal diagnosis [8].

Barriers to Early Intervention in Academic Settings

Despite the evidence, early identification programs in schools and universities continue to rely on community referrals or visible distress to trigger intervention [11]. Unlike sports clubs or workplace wellness programs, where behavior change or performance decline prompts attention, educational institutions often fail to refer students based on early warning signs of emotional or behavioral dysfunction. Institutional inertia, privacy concerns, and lack of trained staff further hinder systematic early screening. Stigma delays treatment seeking, reduces treatment adherence, and increases the risk of complications, highlighting the importance of systematically measuring stigma in clinical settings [12].

Digital Screening and Multidimensional Tools

Emerging research supports the use of digital tools to assess mental health at scale, especially in low-resource settings. Digital applications offer the advantages of cost-efficiency, anonymity, repeatability, and the ability to gather multi-domain data without immediate clinical oversight. Tools that screen across multiple symptom dimensions (e.g., mood, anxiety, psychotic-like experiences, attention, and functioning) are better positioned to capture the complexity of early psychopathology [13,14].

Multidimensional assessments—especially those adapted for mobile or online platforms—can serve as triage instruments to flag at-risk students and direct them to appropriate care. They bridge the gap between community-based awareness and formal clinical evaluation, creating a viable early warning system within educational ecosystems.

The literature supports the assertion that the current clinical paradigm, focused on diagnosing and treating mental disorders, is insufficient for timely and effective early intervention among students. Subclinical symptom clusters present significant risks and deserve attention [15]. Digital, symptom-based, multidimensional screening tools represent a promising innovation in bridging this gap, particularly in resource-limited academic environments.

This paper presents empirical findings from a university-based mental health project in Mumbai.

Methods

Participants and Setting

The study involved 442 engineering students enrolled at K.J. Somaiya Institute of Technology, Mumbai. Participation was voluntary, and informed consent was obtained from all students. The study protocol was reviewed and approved by the institutional ethics committee to ensure compliance with ethical standards.

Instruments

The assessment utilized the MASS (Mental Health Assessment Scales for Students) battery, comprising six validated psychometric scales designed to capture a broad spectrum of mental health dimensions:

- ***Scale for Psychological Stress (13-item)*** *– measuring the students' subjective experience of stress.*
- ***Psychiatric warning Symptoms Scale (10-item)*** *– assessing common psychological symptoms.*
- ***Mental health symptoms (psychopathology) (21-item)*** *– identifying factors contributing to mental health risk.*
- ***Mental health Risk (6-item)- for non-modifiable risk***
- ***Resilience and well-being Scale (24-item)*** *– evaluating protective factors and coping capacity.*
- ***Functioning and well-being Scale*** *(22-item) – measuring daily functioning and impairment.*

Procedure

Data collection was carried out through digital self-assessment administered in a controlled, supervised classroom setting to ensure standardized conditions. Upon completion of the assessments, students received immediate automated feedback tailored to their individual scores. Based on a predefined tiered algorithm, students were triaged and referred for further evaluation or support if indicated.

Data Analysis

Quantitative data were analyzed using statistical software. Chi-square tests were applied to examine categorical relationships, while Pearson correlation coefficients assessed the strength and direction of associations between continuous variables across the scales. Additionally, K-means clustering analysis was employed to identify distinct subgroups of students based on the severity and patterns of mental health indicators, facilitating targeted intervention planning. Descriptive statistics were computed for prevalence estimates. Cross-tabulations and comparative analyses were performed to examine the added value of multidimensional screening over single-domain approaches. Inferential statistics (e.g., chi-square tests, correlation analyses) were used to evaluate associations between domains. All analyses were conducted using SPSS version 27.

Results

Prevalence of Mental Health Symptoms

The screening revealed a high burden of mental health concerns among university students:

- **Stress** was reported by **76%** of participants, with **14.3%** meeting the criteria for *severe stress*.
- **Psychiatric symptoms** were reported by **39.2%**, of whom:
- **6.8%** had *severe psychiatric symptoms*, including depressive features, paranoia, perceptual distortions, and significant emotional dysregulation.
- **5.4%** met 'red-flag' criteria, indicating *high-risk symptoms* such as suicidal ideation, hallucinations, or behavioral disorganization—warranting immediate clinical evaluation.
- **Low psychological resilience** was found in **31%**, suggesting inadequate coping capacity and increased vulnerability to stress-related disorders.
- **Functional impairment**—defined as disruptions in academic, interpersonal, or daily role functioning—was reported by **36.6%** of participants.

2. Added Value of Multidimensional Screening

Analysis demonstrated that a single-domain screening approach (e.g., stress-only) would have identified just **14.3%** of students for further intervention. In contrast, multidimensional assessment identified an *additional 21.1%* of students with clinically significant psychiatric symptoms—including severe emotional dysregulation, hallucinations, or suicidal ideation—who would have been missed by stress-based screening alone.

Similarly, **functional impairment** was not consistently aligned with stress scores. Of those who reported poor functioning, a substantial proportion did not meet the threshold for severe stress, suggesting that **functional decline can occur independently of perceived stress**.

These findings highlight the **non-redundant nature** of each domain, affirming that stress, psychiatric symptoms, resilience, and functioning each contribute independently to risk profiling. Correlation analyses supported these distinctions, confirming that a **multidimensional approach provides a more comprehensive and sensitive identification** of at-risk individuals.

Table 1: Prevalence and Descriptive Summary of Mental Health Variables in University Students (N = 442).

Variable	Percentage (%) / Mean (SD)	Notes
Stress (Any Level)	76.0%	Self-reported stress; based on validated stress scale
└ Severe Stress	14.3%	Scores above clinical cut-off
Psychiatric Symptoms (Any)	39.2%	Includes anxiety, depression, paranoia, and perceptual disturbances
└ Severe Psychiatric Symptoms	6.8%	High symptom burden across domains
└ "Red-Flag" Symptoms	5.4%	Includes suicidality, hallucinations, gross behavioral dysfunction
Low Resilience	31.0%	Scores below standardized resilience threshold
Functional Impairment	36.6%	Impairment in academic, social, or daily life domains

Table 2: Correlation Matrix of Core Mental Health Constructs.

Variables	Stress	Psychiatric Symptoms	Low Resilience	Functional Impairment
Stress	–	0.62***	-0.44***	0.56***
Psychiatric Symptoms		–	-0.49***	0.58***
Low Resilience			–	-0.41***
Functional Impairment				–

Note: ***p* < 0.001**

Table 3: Added Value of Multidimensional Screening: Prevalence of Symptom Clusters and Missed Cases by Stress-Only Screening.

Symptom Cluster	Prevalence (%)	Detected Only via Multidimensional Screening (%)	p-value (vs. Stress-Only Screening)
Severe stress	14.3	—	—
Severe psychiatric symptoms	6.8	4.9	< 0.001
Red-flag symptoms (hallucinations, suicidality)	5.4	4.2	< 0.001
Low resilience	31.0	18.7	< 0.001
Functional impairment	36.6	22.3	< 0.001
Any psychiatric symptom or impairment	44.8	30.5	< 0.001

Table 4: Pearson Correlation Coefficients Between Mental Health Domains.

Construct Pair	Correlation Coefficient (r)	Significance
Stress and Psychiatric Symptoms	0.62	p < 0.001
Psychiatric Symptoms and Functional Impairment	0.58	p < 0.001
Low Resilience and Psychiatric Symptoms	-0.49	p < 0.001
Stress and Low Resilience	-0.44	p < 0.001

Table 5: Gender Distribution of Participants (N = 442).

Gender	Frequency (n)	Percentage (%)
Male	189	42.8%
Female	246	55.7%
Non-binary/Other	7	1.6%
Total	442	100.0%

Note:

Due to ethical considerations regarding anonymity and confidentiality, no additional demographic information (e.g., age, academic course, socioeconomic background) was collected during the digital screening process.

Discussion

This study provides robust evidence that **multidimensional digital screening** offers significantly greater sensitivity for identifying early-stage mental health challenges among university students than conventional single-domain tools.

A key finding is that **over 30% of students** displayed significant functional or psychiatric symptoms without corresponding high stress levels. This suggests that relying solely on stress assessments—as is common in many university wellness programs—may overlook a substantial portion of students with emerging mental health needs.

This aligns with prior research showing that **stress is not a reliable standalone proxy** for psychological dysfunction [4], reporting that students with emotional or functional difficulties often underreport stress, particularly when symptoms are internalized or normalized in academic cultures. Similarly, Kessler et al. (2005) showed that **subclinical symptoms** such as disturbed sleep, paranoia, or affective instability often precede diagnosable mental disorders in young adults by several months to years [7].

The detection of **red-flag symptoms in 5.4%** of students—such as suicidality or hallucinations—is especially concerning. These symptoms are often missed by general stress checklists or wellness surveys, which lack the depth to capture **psychotic or dissociative phenomena** [16]. This underscores the **clinical necessity** of screening tools that assess core psychiatric domains beyond common indicators of distress.

Our findings further validate emerging models in **preventive psychiatry**, which advocate for identifying **trajectories of psychopathology** rather than waiting for full-threshold disorders to manifest [14,17]. Multidimensional frameworks enable the early identification of students exhibiting signs of vulnerability, including emotional dysregulation, low resilience, and declining academic or social functioning—even in the absence of acute stress.

In line with **Keyes' dual continua model** (2002), our findings support the view that mental health encompasses both the presence of well-being and the absence of illness [18]. Patel et al. (2007) further argue that health promotion efforts must target **emotional, psychological, and social well-being**, not merely the reduction of pathology [19]. Notably, **31% of students** in our sample showed low resilience—highlighting the **predictive utility of resilience** as a screening dimension [20].

The use of a digital platform facilitated **large-scale, confidential, and user-friendly assessment**, particularly suited for student populations where **stigma and access barriers** often delay help-seeking. Digital tools have proven effective in mental health care delivery across settings [21,22], and our study adds to this growing body of evidence.

Taken together, these results reinforce the hypothesis that **early-stage mental health concerns are multidimensional and interdependent**, and thus best captured through integrated, symptom-centric screening frameworks. By moving beyond narrow constructs such as stress, multidimensional digital tools can more accurately detect **vulnerable yet underserved subgroups**, enabling timely interventions.

This study presents strong evidence that **multidimensional digital mental health screening** is substantially more effective than traditional single-domain tools—such as stress-only checklists—in identifying at-risk university students. Notably, over **30% of students** exhibited functional or psychiatric impairments despite reporting low stress levels. This finding demonstrates that reliance on stress-centric assessments may lead to significant under-detection of students in need of support.

Moreover, the correlations observed between psychiatric symptoms, stress, functional decline, and **low resilience** suggest that these variables, while interconnected, capture **distinct facets of mental well-being**. For example, some students maintained academic performance despite emotional dysregulation, while others showed functional impairments despite lacking diagnosable psychiatric symptoms. These findings support a **dimensional model of mental health**, where various domains of distress and strength interact to shape overall well-being.

The findings of this study underscore the value of a **multidimensional digital screening approach** in identifying students at psychological risk, especially those who might otherwise be missed by single-domain tools. While each scale within the MASS (Mental Health Assessment Scales for Students) framework—covering stress, psychiatric symptoms, functioning, resilience, and positivity—can be individually interpreted, the real strength lies in their **collective diagnostic yield**. When interpreted together, these domains provide a richer, more clinically relevant understanding of student mental health status.

Although we do not currently have comparative longitudinal data to irrefutably demonstrate that referrals made through this approach are significantly earlier or substantially different in nature, practical experience within university settings strongly suggests so. For instance, the **detection of psychiatric symptoms, moderate-to-severe stress, and impaired functioning** in students who did not self-identify as distressed emphasizes the **limitation of relying solely on overt distress or community referrals--a**, finding echoed by Rickwood et al. (2005) and Eisenberg et al. (2009) [23,3].

In our study, **31% of students were referred for counseling**, and **6% were flagged for psychiatrist referral**. These figures are notably higher than typical help-seeking rates in the literature, which often remain below 20% for counseling and below 2% for psychiatric consultations in similar populations [2,1]. This suggests that **MASS enables earlier and more proactive referrals** by detecting patterns of distress before they evolve into diagnosable disorders. Importantly, the prevalence rates of stress and symptoms in our sample are consistent with existing data [8,1], but the **enhanced referral rates likely reflect the additional value of assessing functional impairment and resilience**—domains not usually emphasized in routine screening.

Functioning emerged as a particularly powerful predictor of referral, aligning with recent evidence that **functional impairment, even in the absence of severe symptoms, is a critical marker of early psychopathology**. This aligns with dimensional models of mental health (Insel et al., 2010), which argue for **the early detection of symptom clusters rather than categorical disorders**. Indeed, many students flagged by MASS showed **subthreshold symptoms**, a clinical gray zone often linked to future risk [24,25].

The **algorithm-driven recommendations** used in MASS appear effective not only in triaging but also in **motivating students to engage with support services**. Guided decision-making rooted in validated metrics can reduce resistance to seeking help, especially in stigmatized environments like universities. The high referral rate thus represents not only better detection but also **enhanced compliance**—a key goal in early intervention.

From a systems perspective, this approach offers notable advantages: **ease of administration, data security, and confidentiality**, which are essential for student participation. Unlike fragmented or subjective triage systems, MASS provides a **standardized, scalable, and evidence-based method for early intervention**—an urgent need in academic institutions grappling with increasing mental health burdens [26].

Finally, the validity and reliability of the MASS instruments—reported elsewhere—further enhance their utility. With strong psychometric foundations, the screening tool offers **credible, reproducible, and clinically interpretable results**, reinforcing its value as a **population-level mental health strategy** in educational settings.

These results reinforce a central limitation of unidimensional screening approaches: **stress is not a reliable proxy for**

psychological distress or dysfunction. As Eisenberg et al. (2009) observed, many students experiencing emotional or functional impairment underreport stress, particularly when internalizing symptoms such as sadness, anxiety, or detachment are normalized within competitive academic cultures [2]. Similarly, Kessler et al. (2005) found that **subclinical psychiatric symptoms**—including insomnia, irritability, or concentration issues—often precede full-threshold disorders by months or years, particularly among emerging adults [8].

A particularly concerning finding was the presence of **"red-flag" psychiatric symptoms in 5.4% of students**, including suicidal ideation and perceptual disturbances (e.g., hallucinations). These symptoms typically fall outside the scope of stress assessments or wellness surveys, which rarely screen for psychosis, dissociation, or severe affective dysregulation. This diagnostic blind spot highlights the need for tools that assess **core psychiatric domains**, as emphasized by Rössler et al. (2011) [16].

The study's findings align with contemporary frameworks of **early intervention and preventive psychiatry**, which emphasize symptom progression and dimensional assessment over categorical diagnoses. Fusar-Poli et al. (2013) and McGorry et al. (2014) underscore the necessity of recognizing prodromal and attenuated symptoms in youth populations, and not just diagnosale disorders [13,17]. A multidimensional tool is uniquely suited to this task, capturing nuanced patterns across **stress, mood, cognition, functioning, and resilience**.

This view is supported by Keyes' (2002) **mental health continuum model**, which emphasizes flourishing and languishing as part of a broad spectrum of psychological states—not merely the absence or presence of mental illness [18]. Likewise, Patel et al. (2007) stresses the importance of integrating social and emotional well-being in youth mental health strategies. Importantly, **31% of participants** in the present study demonstrated **low resilience**, a known risk factor for the onset and chronicity of mental illness [19]. Including resilience in screening tools enhances **predictive power and responsiveness to early interventions**.

The digital nature of the screening platform also proved advantageous. Digital tools allow for **scalable, confidential, and real-time screening**, especially in university environments where stigma, cost, and time constraints often act as barriers to care. Previous research by Lattie et al. (2019) and Naslund et al. (2017) confirms that **digital assessments can reliably engage hard-to-reach populations** and facilitate early detection [21,22]. When paired with validated scales and algorithmic triaging, such tools offer an efficient alternative to traditional clinical interviews—especially for large populations.

Taken together, these findings support the hypothesis that **early indicators of mental disorders are best detected through multidimensional frameworks**, particularly in transitional life stages like university. Kessler and Üstün (2008) and Jones (2013) both emphasize that **most adult mental health disorders begin before age 25**, making this window crucial for intervention. [9,24] A shift from reactive diagnosis to **proactive identification of emerging risk** is essential in preventing long-term mental health deterioration.

In conclusion, this study contributes to a growing body of literature advocating for **comprehensive, digital, and preventive mental health models**. It urges a move away from narrow screening approaches and towards **integrative tools** that can capture the complexity and early signs of student mental health concerns—thereby enhancing access, precision, and impact of mental health services in educational settings.

Implications for Practice and Policy

To enhance early identification and support for student mental health, institutions should adopt **multidimensional screening programs** that assess a broad range of psychological factors, rather than relying solely on stress or depression-specific tools. Such an approach ensures that individuals who do not report high stress but experience other significant symptoms—such as low resilience, impaired functioning, or early psychiatric indicators—are not overlooked.

Incorporating **digital screening tools into routine university health systems** can facilitate timely and systematic identification, monitoring, and referral of students in need. These tools offer scalability, accessibility, and confidentiality, which are critical in reducing stigma and improving participation in mental health programs.

Furthermore, screening efforts must be connected to **scalable intervention strategies**, including digital psychoeducation, virtual counseling, and telehealth-based referrals. This integration ensures that identification is not an isolated process but leads to meaningful and supportive follow-up care.

Finally, there is a pressing need for **policy-level recognition and support** for population-based mental health surveillance. Policymakers should prioritize the development and implementation of culturally sensitive, accessible, and evidence-based digital platforms to support early mental health intervention efforts across educational institutions.

Limitations and Future Directions

While the digital screening tool demonstrated high yield, it does not replace clinical diagnosis. Further studies are needed to validate symptom detection against structured psychiatric interviews. Longitudinal tracking of students identified as high-risk would help assess the predictive validity of multidimensional screening for the onset of clinical disorders. Additionally, the role of environmental and academic factors in moderating outcomes warrants deeper exploration.

Conclusion

Relying solely on clinical diagnosis undermines the objectives of early intervention. This study demonstrates that a digital, multidimensional framework enables earlier detection and tiered support. The MASS model offers a promising approach for proactive, non-stigmatizing, and scalable mental health care in academic institutions.

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