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1



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Table of Contents

<i>Chapter 1: Artificial Intelligence Adoption and Operational Efficiency in Modern Business Enterprises</i>	1
<i>Chapter 2: Artificial Intelligence and Emerging Practices in English Language Learning</i>	10
<i>Chapter 3: Artificial Intelligence Assisted Learning and Academic Achievement among University Students</i>	17
<i>Chapter 4: Behavioural Biases and Portfolio Decisions among Individual Equity Investors</i>	25
<i>Chapter 5: Changing Family Structures and Intergenerational Relationships in Urban Communities</i>	34
<i>Chapter 6: Collaborative Learning Practices and Critical Thinking Skills among Secondary Students</i>	41
<i>Chapter 7: Cyberbullying Experiences and Psychological Adjustment among University Students</i>	49
<i>Chapter 8: Digital Assessment Literacy among Teachers in Secondary Education</i>	56
<i>Chapter 9: Digital Citizenship Education and Responsible Technology Use among Adolescents</i>	63
<i>Chapter 10: Digital Portfolio Assessment and Reflective Learning among Undergraduate Students</i>	71
<i>Chapter 11: Emotional Intelligence and Coping Strategies among College Students</i>	78
<i>Chapter 12: Family Communication and Emotional Regulation among Adolescents</i>	85
<i>Chapter 13: Inquiry-Based Learning and Scientific Reasoning among School Students</i>	93
<i>Chapter 14: Interactive Multimedia Learning and Conceptual Understanding among Secondary Students</i>	102
<i>Chapter 15: Media Literacy Education and Critical Awareness among Adolescent Learners</i>	111
<i>Chapter 16: Metacognitive Learning Strategies and Academic Performance among College Students</i>	118
अध्याय 17: NEP 2020 के परिप्रेक्ष्य में उच्च शिक्षा में अकादमिक बैंक ऑफ क्रेडिट की उपयोगिता	125
अध्याय 18: NEP 2020 के संदर्भ में शिक्षा में कौशल विकास और भविष्यपरक रोजगार तैयारी का अध्ययन	131
<i>Chapter 19: Online Assessment Practices and Student Learning Outcomes in Higher Education</i>	137
<i>Chapter 20: Peer Feedback and Academic Writing Development among University Students</i>	145
<i>Chapter 21: Peer Support and Psychological Adjustment during Early Adulthood</i>	152
<i>Chapter 22: Teacher Feedback Practices and Student Academic Motivation in Secondary Education</i>	159
<i>Chapter 23: Teacher Leadership and School Improvement in Contemporary Educational Institutions</i>	167
<i>Chapter 24: Teacher Work Engagement and Instructional Quality in Higher Education</i>	176
<i>Chapter 25: Virtual Learning Environments and Student Satisfaction in Higher Education</i>	184
Chapter 26: Work-Life Balance and Mental Well-Being among Working Adults	192

Chapter 27: Working Capital Management and Financial Performance of Small and Medium Enterprises	200
अध्याय 28: आधुनिक हिंदी साहित्य में हाशिए के समुदायों की अभिव्यक्ति और पहचान	208
अध्याय 29: उच्च शिक्षा में डिजिटल नागरिकता और उत्तरदायी प्रौद्योगिकी उपयोग व्यवहार का अध्ययन	215
अध्याय 30: गृह विज्ञान एवं खाद्य प्रौद्योगिकी के माध्यम से घरेलू खाद्य सुरक्षा और सतत पोषण प्रबंधन का मूल्यांकन	222
अध्याय 31: ग्रामीण शिक्षा में तकनीकी संसाधनों की उपलब्धता और शैक्षिक अवसरों का विश्लेषण	229
अध्याय 32: नई शिक्षा व्यवस्था में हिंदी भाषा शिक्षण की उभरती प्रवृत्तियाँ	234
अध्याय 33: प्रारंभिक शिक्षा में गतिविधि आधारित शिक्षण और अवधारणात्मक समझ के विकास का विश्लेषण	240
अध्याय 34: मानवाधिकार और कानून के परिप्रेक्ष्य में कृत्रिम बुद्धिमत्ता आधारित निगरानी की संवैधानिक समीक्षा	247
अध्याय 35: विद्यालयी शिक्षा में अनुभवात्मक शिक्षण और विद्यार्थियों की रचनात्मक क्षमता का संबंध	253
अध्याय 36: विद्यालयी शिक्षा में डिजिटल कहानी कथन और रचनात्मक अभिव्यक्ति के मध्य संबंध	260
अध्याय 37: विद्यालयी शिक्षा में सहयोगात्मक अधिगम और सामाजिक कौशल विकास का विश्लेषण	268
अध्याय 38: शिक्षा में माइक्रोलर्निंग रणनीतियों द्वारा ज्ञान प्रतिधारण और अधिगम दक्षता का अध्ययन	275
अध्याय 39: शैक्षिक मनोविज्ञान में बुद्धिलब्धि, भावनात्मक बुद्धिमत्ता और शैक्षणिक अनुकूलन का तुलनात्मक अध्ययन	282
अध्याय 40: समावेशी शिक्षा में सहायक प्रौद्योगिकी द्वारा विशेष आवश्यकता वाले विद्यार्थियों का सशक्तीकरण	289

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International Conference On Multidisciplinary Research

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Chapter 7: Cyberbullying Experiences and Psychological Adjustment among University Students

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Abstract — Cyberbullying has become an important digital-health concern in higher education as interpersonal aggression increasingly extends across social networking, messaging, gaming, and university-linked online environments. This study examines how the severity, repetition, and modality of cyberbullying experiences relate to multidimensional psychological adjustment among university students rather than treating victimization as a simple binary exposure. A central research gap is the limited integration of cyberbullying exposure, psychological adjustment indicators, digital-behaviour characteristics, and protective psychosocial factors within a unified computational framework for university populations.

The proposed research conceptualizes psychological adjustment through emotional distress, self-esteem, perceived social connectedness, coping capacity, and academic-functional adaptation. A multimodal analytical framework combining validated self-report measures with structured digital-behaviour indicators is proposed to characterize heterogeneous victimization profiles.

Keywords — Cyberbullying, Psychological Adjustment, University Students, Digital Mental Health, Machine Learning, Digital Resilience

Introduction

Digital communication is embedded in contemporary university life. Students use social networking platforms, instant messaging applications, learning-management systems, online discussion spaces, collaborative applications, and digital communities for academic coordination and interpersonal interaction. These technologies provide substantial educational and social benefits, yet they also create channels through which interpersonal aggression can persist beyond conventional spatial and temporal boundaries. Cyberbullying may involve repeated hostile messaging, humiliation, rumor dissemination, impersonation, exclusion, threatening communication, unauthorized distribution of personal material, or other digitally mediated actions intended to cause distress or social harm.

The relevance of this phenomenon to higher education has become increasingly apparent. University students occupy a developmental period characterized by increasing autonomy, changing peer networks, academic demands, identity development, and extensive digital participation. Consequently, cybervictimization may intersect with several dimensions of psychological functioning rather than producing a uniform clinical response. A recent systematic review specifically examining college and university populations synthesized 32 studies involving 29,593 students and found recurring associations between cybervictimization and depression,

anxiety, stress, reduced self-esteem, suicidal behaviour, fear, and impaired academic concentration or productivity.

Broader international evidence also demonstrates why digitally mediated peer aggression warrants continued investigation. The World Health Organization's 2021/2022 Health Behaviour in School-aged Children study reported that approximately 15% of surveyed adolescents across 44 countries and regions had experienced cyberbullying, with reported victimization increasing compared with 2018. Although these data concern younger populations rather than university students, they demonstrate that cybervictimization is already established before many individuals enter higher education. WHO data additionally indicate that problematic social-media behaviour increased among adolescents between 2018 and 2022, reinforcing the importance of studying the psychological implications of rapidly evolving digital environments.

Cyberbullying differs from many traditional forms of interpersonal aggression because harmful content may be persistent, rapidly disseminated, repeatedly viewed, or encountered in environments that victims use daily. A humiliating post, altered image, threatening message, or exclusionary group interaction may remain accessible after the original event. Audience size can also be uncertain, while anonymity or pseudonymity may make the source of aggression difficult to establish. Consequently, the psychological meaning of cybervictimization cannot necessarily be inferred from event frequency alone.

University research is particularly important because much of the historical bullying literature has concentrated on children and adolescents. Recent scholarship has begun to address this imbalance. Bussu and colleagues' systematic review of cyberbullying and cyberstalking among university students screened 7,518 records and included 61 studies, identifying psychological vulnerability, previous face-to-face victimization, risky digital behaviour, demographic factors, and patterns of help seeking among relevant themes. The authors also highlighted continuing gaps concerning the effectiveness of institutional policies and prevention programmes in higher education.

A second limitation concerns outcome conceptualization. Existing research frequently concentrates on individual adverse outcomes—particularly depression, anxiety, stress, or suicidal behaviour. These outcomes are essential, but **psychological adjustment** is broader. An individual may exhibit moderate emotional distress while maintaining academic functioning and supportive relationships; another may report limited clinical symptomatology yet experience social withdrawal, diminished self-worth, maladaptive coping, or deterioration in academic engagement. Treating adjustment as a multidimensional

construct therefore permits a more differentiated analysis of how students respond to cyberbullying.



Fig. 1: Cyberbullying Awareness

A third issue is analytical. Conventional correlational and regression methods remain valuable for estimating associations and testing theoretically specified relationships, but cyberbullying experiences may involve nonlinear and interactive processes. The effect of repeated anonymous harassment, for example, may depend simultaneously on exposure frequency, perceived severity, social support, coping style, prior victimization, online activity, and the student's capacity to manage adverse digital interactions. Such relationships provide a rationale for combining conventional statistical inference with interpretable machine-learning techniques rather than positioning the two approaches as alternatives.

The proposed study therefore introduces an **exposure–resilience–adjustment framework**. Cyberbullying is represented through multiple exposure dimensions, including recurrence, perceived intensity, public visibility, anonymity, and modality. Psychological adjustment is represented through emotional, self-evaluative, social, coping, and academic-functional dimensions. Protective variables—particularly perceived social support, adaptive coping, and digital resilience—are positioned as potential buffers. Machine-learning methods in Part 2 will be used to test whether multidimensional information improves identification of high-risk adjustment profiles and to determine which combinations of factors contribute most strongly to prediction.

Research Gap and Objective

The distinctive gap addressed by this manuscript is therefore not merely whether cyberbullying correlates with psychological distress. Current evidence already supports such an association. The unresolved problem is whether **heterogeneous characteristics of cyberbullying exposure can be integrated with resilience and digital-behaviour indicators to explain multidimensional psychological adjustment among university students using an interpretable computational framework**.

Accordingly, the primary objective is to develop and evaluate a framework capable of distinguishing students with resilient, moderately affected, and high-risk adjustment profiles following varying cyberbullying experiences. A secondary objective is to determine whether protective psychosocial characteristics modify the relationship between exposure intensity and psychological adjustment. The computational component is designed for risk stratification and explanatory analysis rather than automated clinical diagnosis.

Literature Review

Cyberbullying in the Higher-Education Context

Cyberbullying research initially developed primarily around school-age populations, but university environments present a distinct social and technological context. Students typically have greater autonomy over technology use, interact across multiple digital networks, and may simultaneously participate in academic, professional, friendship, and anonymous online communities. Cyberbullying during this stage can therefore cross institutional and personal boundaries.

Earlier systematic scholarship specifically noted that university students had received less research attention than school students despite their substantial reliance on information and communication technologies. Reviews of university cyberbullying subsequently identified interacting personal, psychological, socio-cognitive, and environmental factors, suggesting that simplistic explanations based only on frequency of internet use are inadequate.

More recent research has strengthened this argument by considering victim-specific vulnerability mechanisms. For example, Yang, Huang, and Li investigated attachment anxiety and cyberbullying victimization among college students through social-media self-disclosure and gender-related moderation, illustrating how interpersonal characteristics and online behaviour may jointly shape exposure risk. Such findings support a transition from single-variable explanations toward interaction-based models.

Cybervictimization and Emotional Distress

Among the most consistently investigated consequences of cybervictimization are depression, anxiety, and stress. Arif et al.'s 2024 systematic review found significant associations with depression in 16 of 20 included studies assessing that outcome and with anxiety in 12 of 15 studies. All three studies evaluating stress reported a significant relationship with cybervictimization. The review also identified associations involving suicidal behaviour, lower self-esteem, fear of perpetrators, substance use, and reduced academic concentration or productivity.

These findings establish psychological distress as an important consequence but simultaneously reveal substantial heterogeneity across studies. Variation can originate from sampling strategies, cyberbullying definitions, measurement instruments, cultural environments, exposure duration, and differences in students' coping resources. Consequently, the presence of an association does not imply that every cybervictimized student follows an equivalent psychological trajectory.

The present study therefore avoids conceptualizing cyberbullying as a deterministic precursor of mental disorder. Instead, cybervictimization is treated as a psychosocial stressor whose consequences may vary according to exposure characteristics and personal and social resources.

Self-Esteem, Social Functioning, and Adjustment

Self-esteem is especially relevant because cyberbullying frequently targets identity, appearance, competence, relationships, or social reputation. Repeated negative digital feedback can potentially alter self-evaluation even when severe clinical symptoms are absent. The systematic evidence summarized by Arif et al. found weak but statistically significant negative correlations between cybervictimization and self-esteem in several included studies.

Social functioning constitutes another important dimension. Online aggression may encourage avoidance of particular platforms, withdrawal from peer networks, reluctance to communicate, or heightened vigilance in digital interactions. At the same time, supportive relationships can provide emotional validation and practical assistance. Bussu et al. identified seeking support from family and friends among the protective responses described in university-focused literature.

This distinction is important for psychological-adjustment research. The relevant question is not solely whether distress rises following cybervictimization but whether students retain functional social relationships, self-confidence, coping resources, and participation in academic life.

Digital Exposure and the Contemporary Social-Media Environment

The digital context surrounding cyberbullying has changed rapidly. Communication now moves between private messaging, public social networks, group chats, multimedia platforms, gaming communities, and educational systems. Exposure is therefore better conceptualized as a pattern than as a single event category.

WHO's recent international evidence demonstrates the growing relevance of online interaction to young people's well-being. Its 2024 reporting showed increases in both cyberbullying victimization and perpetration among adolescents compared with the previous HBSC survey cycle. Separate HBSC findings showed that problematic social-media use rose from 7% in 2018 to 11% in 2022 among surveyed adolescents. Importantly, WHO also noted that digital engagement itself is not inherently harmful: heavy but non-problematic users could report strong peer support and social connection.

This distinction has methodological implications. Screen time or social-media frequency should not automatically be

interpreted as proxies for cyberbullying exposure or psychological harm. The proposed framework consequently distinguishes general digital engagement from harmful interpersonal experiences.

Resilience and Protective Processes

A major limitation of deficit-oriented cyberbullying research is that it can underrepresent the factors explaining why some exposed students maintain comparatively healthy functioning. Psychological adjustment depends partly on the resources available after an adverse experience. Social support may reduce isolation; adaptive coping may facilitate problem solving; digital literacy may assist students in blocking, documenting, reporting, or disengaging from abusive interactions; and digital resilience may help restore functional online participation.

The university-focused systematic literature supports greater attention to protective factors and institutional intervention. Bussu et al. emphasized support-seeking and preventive institutional engagement, while Alpochoritis' review of university-level prevention literature concluded that prevention programmes within higher education require greater development and implementation.



Fig. 2: The Emotional Impact of Cyberbullying

The current research therefore treats resilience not as the absence of distress but as the capacity to preserve or recover psychological and functional adjustment despite adverse digital experiences.

Artificial Intelligence and Interpretable Risk Modelling

The multidimensional structure of cyberbullying makes it suitable for computational analysis, provided that algorithmic outputs are interpreted cautiously. Traditional statistical models can quantify prespecified associations, whereas machine-learning algorithms can detect nonlinear thresholds and higher-order interactions that may otherwise remain obscured. For instance, recurrent cybervictimization combined with weak social support and maladaptive coping may carry different implications from the same exposure frequency in a student with strong protective resources.

However, predictive accuracy alone is insufficient for digital mental-health applications. Black-box classification may provide limited value to counsellors or university support services if the factors underlying a prediction cannot be inspected. The proposed methodology therefore emphasizes **interpretable machine learning**, with feature-attribution methods used to identify the variables driving model predictions. The model is not intended to diagnose psychiatric conditions or replace professional assessment. Instead, it provides a research instrument for identifying patterns associated with poorer adjustment and for testing whether exposure and resilience information contributes incremental predictive value.

Proposed Methodology

The proposed study adopts a **cross-sectional, multimodal predictive design** integrating psychometric assessment, self-reported digital-behaviour indicators, and interpretable machine learning. Rather than predicting whether a student has experienced cyberbullying, the framework estimates the degree of psychological maladjustment associated with different patterns of cybervictimization.

Recent systematic evidence confirms that cybervictimization among university students is associated with depression, anxiety, stress, lower self-esteem, and impaired academic functioning. At the same time, recent university mental-health research demonstrates the feasibility of combining machine-learning models with SHAP-based interpretability to investigate complex relationships between psychological, interpersonal, and behavioural factors.

The conceptual framework contains three domains. The **exposure domain** captures cyberbullying frequency, recurrence, anonymity of the aggressor, public visibility, perceived severity, and the number of digital channels through which victimization occurs. The **protective-resource domain** incorporates perceived social support, adaptive coping, digital resilience, and willingness to seek assistance. The **adjustment domain** incorporates emotional distress, self-esteem, social connectedness, and academic-functional adjustment.

Psychological adjustment is operationalized as a composite score after standardization and directional harmonization of the constituent measures. Higher values represent greater maladjustment. For predictive classification, scores are divided into three empirically determined profiles—**resilient adjustment, moderate vulnerability, and high-risk maladjustment**—using latent profile analysis followed by stability testing. This approach avoids imposing arbitrary symptom cut-offs on a construct intended to capture broader psychological functioning.

Importantly, the numerical findings below constitute a **proposed experimental specification and expected reporting structure, not observations from an actually collected dataset**. They should be replaced with empirical values if the manuscript is submitted as completed primary research.

Experimental Setup

Dataset

The experimental design specifies a target sample of **684 university students aged 18–29 years**, recruited from undergraduate and postgraduate programmes across multiple academic disciplines. Stratified recruitment would be used to avoid excessive representation of a single programme or year of study.

Eligibility requires current university enrolment, regular use of at least one internet-based communication platform, and informed consent. Responses showing extensive missingness, implausibly short completion time, or invariant responding across psychometric items would be excluded before modelling. The feature matrix would contain four broad groups: cyberbullying exposure characteristics, psychological resources, digital-behaviour characteristics, and demographic/academic covariates. No private message content, passwords, direct identifiers, or covertly harvested social-media data would be collected.

Data Preprocessing

Initial processing begins with duplicate-response detection and range validation. Missing numerical values below a predetermined threshold would be imputed within training folds using median imputation, while categorical variables would use the most frequent category or an explicit missing category where theoretically appropriate. This fold-specific strategy prevents information leakage from the test set.

Continuous features would be standardized for models sensitive to feature magnitude. Highly redundant predictors would be examined using correlation analysis and variance-inflation diagnostics. Categorical features would be appropriately encoded, while ordinal exposure variables would retain their inherent ordering.

Because high-risk psychological maladjustment is expected to represent a smaller subgroup, class imbalance would be addressed through **class-weighted learning rather than indiscriminate synthetic oversampling**. This decision reduces the possibility of generating artificial psychological profiles that have no direct empirical counterpart.

The final data would be partitioned using stratified sampling into **70% training, 15% validation, and 15% independent test subsets**. All preprocessing parameters would be learned exclusively from training data.

Model Architecture

Four complementary algorithms are proposed.

Elastic-Net Logistic Regression provides an interpretable linear baseline and controls feature redundancy through combined L1/L2 regularization.

Random Forest captures nonlinear relationships and interactions without imposing a predefined functional relationship between cyberbullying exposure and adjustment.

Support Vector Machine with radial-basis kernel models complex decision boundaries in standardized multidimensional feature space.

The principal model is **CatBoost**, a gradient-boosted decision-tree architecture selected for its ability to handle heterogeneous tabular features and complex nonlinear interactions. The model receives exposure severity, recurrence, anonymity, public

visibility, platform multiplicity, social support, coping, digital resilience, online engagement, and demographic/academic characteristics as predictors.

Recent research has successfully applied ensemble machine-learning approaches to university mental-health prediction, while CatBoost has demonstrated utility in modelling psychological distress from heterogeneous student characteristics.

Training Strategy

Model development uses **nested five-fold stratified cross-validation** within the development dataset. Hyperparameters are optimized according to macro-averaged F1 rather than overall accuracy because the three adjustment groups may differ in prevalence.

Early stopping is applied to CatBoost when validation loss no longer improves. Random Forest tuning includes tree number, maximum depth, minimum leaf size, and feature-sampling ratio. SVM optimization considers regularization strength and kernel coefficient. Elastic-Net optimization determines the regularization strength and L1/L2 mixing parameter.

The untouched test subset is evaluated only after final model selection. Bootstrapping with 1,000 resamples is proposed for estimating 95% confidence intervals around principal performance measures.

SHAP values are subsequently calculated for the best-performing tree-based model. The objective is not merely to identify which features are important globally but also to examine why individual students receive different predicted risk probabilities.

Evaluation Metrics

Model performance is assessed using **balanced accuracy, macro-F1, multiclass AUROC, Matthews correlation coefficient (MCC), and expected calibration error (ECE)**. Balanced accuracy evaluates performance across unequal classes, while macro-F1 assigns equal importance to each adjustment profile. MCC provides a robust summary of multiclass classification quality. AUROC evaluates discrimination, and ECE assesses whether predicted probabilities correspond appropriately to observed class frequencies.

Calibration is especially important because a digital-health risk model can have reasonable discrimination while producing poorly calibrated probabilities. The study therefore prioritizes both predictive separation and probability reliability.

Results and Discussion

Under the proposed experimental specification, the expected comparative pattern is that nonlinear ensemble models outperform the linear baseline because cyberbullying consequences are unlikely to operate through simple additive relationships. The illustrative experimental output below demonstrates the form in which the final empirical analysis should be reported.

Table 1. Comparative Performance of the Proposed Psychological-Adjustment Models

Model	Balanced Accuracy	Macro-F1	Multiclass AUROC	MCC	ECE
Elastic-Net	0.711	0.694	0.814	0.556	0.081
SVM-RBF	0.772	0.758	0.861	0.648	0.064
Random Forest	0.801	0.786	0.884	0.691	0.057
CatBoost	0.834	0.821	0.913	0.744	0.039

Model Performance for Psychological-Adjustment Classification

Comparison of balanced accuracy and macro-F1 across the four proposed machine-learning models.



The expected superiority of CatBoost would support the central theoretical proposition that psychological adjustment following cyberbullying is shaped by nonlinear combinations of risk and protective variables rather than exposure frequency alone. A linear model could capture a general dose-response association but may fail to represent situations in which severe exposure has markedly different consequences according to social support or coping capacity.

SHAP analysis would then be used to examine this proposition directly. The anticipated feature hierarchy places **perceived cyberbullying severity, recurrence, social support, adaptive coping, public visibility, and digital resilience** among the strongest contributors. Such a pattern would be theoretically meaningful because it separates the objective structure of exposure from the resources available for responding to it.

A particularly important anticipated interaction concerns recurrence and social support. Repeated cyberbullying combined with weak perceived support would be expected to produce a substantially greater predicted probability of high-risk maladjustment than repeated exposure accompanied by strong support. This would imply that exposure frequency alone provides an incomplete description of vulnerability.

Similarly, public visibility may amplify the psychological implications of cyberbullying because reputational damage and perceived audience size can extend the meaning of an aggressive event beyond the original interaction. Anonymous harassment may operate differently by increasing uncertainty regarding the

perpetrator and potentially extending vigilance into other digital interactions.

The proposed analysis also distinguishes **digital engagement from harmful digital experience**. High platform use should not automatically be interpreted as evidence of psychological risk. Instead, the predictive importance of engagement would be evaluated in interaction with victimization intensity, sleep disruption, support resources, and coping behaviour. This distinction is important because digital communication may simultaneously expose students to harmful interactions and provide access to supportive relationships.

From a digital-health perspective, the most important model output is therefore not simply the highest AUROC. The value of the system lies in identifying interpretable combinations of modifiable factors. For example, a high predicted vulnerability associated primarily with low social support and maladaptive coping has different intervention implications from equivalent predicted vulnerability driven by repeated severe public harassment.

The proposed results would be consistent with the broader literature showing substantial psychological consequences of cybervictimization among university students. A 2024 systematic review involving 32 studies and 29,593 students reported associations involving depression, anxiety, stress, self-esteem, suicidal behaviour, and academic concentration or productivity. More recent research has likewise examined psychological well-being as an important factor in cyberbullying victimization among university students.

At the same time, the computational contribution differs from automated cyberbullying-content detection. Recent deep-learning work has demonstrated that social-media text can be classified for cyberbullying detection with high predictive performance. The present framework instead asks a subsequent and psychologically different question: **given a student's pattern of cyberbullying exposure, which combination of exposure characteristics and resilience resources is associated with poorer psychological adjustment?**

This distinction has practical significance. An institutional system designed only to detect abusive language cannot determine whether a particular student has experienced substantial psychological disruption. Conversely, a psychological-adjustment model cannot establish that a specific digital communication constitutes cyberbullying. The two tasks should therefore remain analytically separate.

Limitations

Several limitations must be considered. First, the cross-sectional design cannot establish temporal causality. Psychological difficulties may increase vulnerability to adverse online experiences while cybervictimization may simultaneously worsen psychological functioning. Longitudinal measurement is required to distinguish these pathways.

Second, cyberbullying and psychological variables depend substantially on self-report and may therefore be influenced by recall bias, interpretation, or social desirability. Third, platform-specific behaviours change rapidly, meaning that individual

digital-platform variables may have limited temporal generalizability.

Fourth, a model trained within a particular university population should not automatically be generalized across countries, cultures, age groups, or institutional environments. External validation is essential before deployment. Finally, algorithmic risk classification must not be treated as a clinical diagnosis. False-positive and false-negative predictions are unavoidable, and psychological support decisions require human assessment.

Future Scope

Future research should transform the framework into a longitudinal design with repeated assessments across academic semesters. Temporal modelling could establish whether changes in cyberbullying exposure precede changes in psychological adjustment and whether protective resources predict recovery.

With explicit informed consent and strong privacy safeguards, future studies could incorporate privacy-preserving digital phenotyping rather than collecting private communication content. Passive sensing has already been investigated as a method for predicting stress in university students, demonstrating the broader potential of behavioural signals in digital mental-health research.

Federated learning could eventually permit multi-university model development without centralizing sensitive student-level data. Fairness analysis should also test whether predictive errors differ across demographic or socioeconomic groups. A further priority is **counterfactual explainability**, which could identify potentially modifiable variables associated with movement from a high-risk prediction toward a lower-risk profile.

The strongest extension would be a prospective intervention study in which students identified through voluntary screening receive different levels of digital-safety education, counselling access, peer support, or resilience-oriented resources. Subsequent changes in adjustment could then determine whether model-guided support provides measurable benefits beyond conventional screening.

Conclusion

Cyberbullying among university students should be examined as a heterogeneous digital stressor rather than a binary experience. The proposed exposure–resilience–adjustment framework integrates the severity, recurrence, modality, anonymity, and visibility of cyberbullying with social support, coping resources, digital resilience, and multidimensional psychological functioning.

The computational component extends conventional association-based research by using interpretable machine learning to examine nonlinear combinations of risk and protection. CatBoost, SHAP-based interpretation, calibration assessment, and conventional statistical analyses together provide a framework in which predictive performance does not replace psychological explanation.

The central implication is that identical levels of cyberbullying exposure need not produce identical adjustment outcomes. Understanding **who experiences difficulty, under what exposure conditions, and in the presence or absence of**

which protective resources is potentially more informative than establishing another general correlation between cyberbullying and distress. With longitudinal validation, ethical safeguards, external replication, and human oversight, such models could contribute to targeted university digital-wellness programmes and earlier identification of students requiring additional support.

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