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Machine-Learning Prediction of Academic Stress from Working Memory Load and Neuroticism Facets

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ABSTRACT

Objective: To employ advanced machine learning algorithms to predict the severity of academic stress among university students by synthesizing metrics of working memory load and specific facets of the neuroticism personality trait.

Methods and Materials: This predictive cross-sectional study evaluated a sample of $N = 452$ Brazilian university students. Data were collected utilizing the Perception of Academic Stress Scale, a dual N-back task to measure working memory capacity, and the NEO Personality Inventory-Revised to assess neuroticism facets. The predictive modeling utilized several machine learning algorithms, with a primary focus on eXtreme Gradient Boosting (XGBoost). The dataset was split into an 80%training set with 10-fold cross-validation and a 20%hold-out test set, and feature importance was interpreted using SHapley Additive exPlanations (SHAP) values.

Findings: The XGBoost algorithm yielded the most robust predictive performance, explaining a significant portion of the variance in the test set ($R^2 = 0.58$, $MAE = 4.12$, $RMSE = 5.36$). SHAP analysis revealed that the Vulnerability to Stress facet was the strongest positive predictor of academic stress (mean absolute SHAP = 2.84), whereas Working Memory Capacity emerged as the strongest negative, protective predictor (mean absolute SHAP = 1.95), specifically when surpassing a standardized threshold of $Z = 0.50$.

Conclusion: Machine learning architectures successfully demonstrate that academic stress is deeply driven by non-linear interactions between a student's intrinsic emotional vulnerability and their momentary cognitive working memory capacity.

Keywords: *Academic Stress, Working Memory, Neuroticism, Machine Learning, Students.*

1. Introduction

Academic stress has emerged as a pervasive and debilitating phenomenon within higher education institutions globally, imposing significant constraints on the psychological well-being and academic trajectories of university students. The rigorous demands of academic curricula, stringent evaluation criteria, and the pressure to secure future career prospects collectively engender an environment where stress is a chronic rather than an episodic experience. In recent years, empirical attention has increasingly focused on the cascading effects of this stress, particularly highlighting how it impairs general mental health, especially among vulnerable demographic groups such as female students in higher education (Imran, 2025). The psychological burden of academic environments is further exacerbated by external systemic shocks, such as the lingering lifestyle disruptions and emotional sequelae associated with the COVID-19 pandemic (Fahim et al., 2022). Furthermore, investigations into adolescent populations have revealed that academic stress severely undermines self-esteem, setting a detrimental precedent for their transition into university life (Shalu et al., 2025). The manifestations of this stress extend beyond psychological discomfort, frequently precipitating severe somatic and physiological disruptions, most notably chronic insomnia and significantly impaired sleep quality (Antony et al., 2025; Rajbahak et al., 2025). Recognizing the severity of these outcomes, universities are increasingly confronted with the necessity of implementing targeted psychological counseling and support systems to address the complex needs of their student populations (Musso et al., 2022). Reducing stress, anxiety, and depression in high-stakes disciplines, such as nursing and health sciences, remains a critical priority for educational policymakers aiming to prevent attrition and foster holistic student development (Aloufi et al., 2021).

When academic stress is left unmanaged or exceeds an individual's coping threshold, it frequently culminates in severe academic burnout, a syndrome characterized by profound emotional exhaustion, cynicism, and a reduced sense of academic efficacy (Singh et al., 2021). The pathway from stress to burnout is complex and often mediated by maladaptive cognitive patterns, such as rumination, which traps students in a cycle of negative self-reflection (Zuo et al., 2024). Unfavorable external social dynamics, such as parental neglect manifesting as "mother phubbing," further exacerbate adolescent burnout by eroding essential emotional support structures, a process heavily moderated by distinct personality variables (Bai et al., 2020). In response to mounting stress, students frequently resort to maladaptive behavioral avoidance strategies, most prominently academic procrastination, which paradoxically increases future stress and significantly compromises overall academic performance (Kuftyak, 2022). To mitigate these adverse outcomes, the cultivation of effective coping strategies and intrinsic resilience is paramount. Research underscores that robust coping mechanisms are instrumental in preserving student resilience amidst academic adversity (Amalianita et al., 2025), and the specific attachment styles individuals form early in life dictate the efficacy of these coping paradigms (Liao, 2025). Active problem-focused coping has been particularly highlighted as essential for specific cohorts, such as nursing students navigating high-pressure clinical and didactic requirements (Samong, 2024). Educational interventions prioritizing the explicit instruction of self-regulation strategies have proven highly effective in enhancing resilience and reducing stress, even among students with historically low academic performance (Pourshalchi et al., 2025). Additionally, addressing concurrent psychological challenges, such as vocational indecision, through resilience-building can significantly alleviate the reciprocal burden of academic stress (Buils & Mateu-Pérez, 2025). Ultimately, establishing robust support networks—encompassing both dedicated teacher mentorship and strong family cohesion—serves as a vital buffer, effectively reducing the probability that chronic academic stress will translate into the ultimate negative outcome of university dropout (Van, 2024).

The capacity to maintain academic engagement in the face of stress is fundamentally tethered to an individual's psychological capital, an amalgam of self-efficacy, optimism, hope, and resilience. Psychological capital serves as a critical mediator, linking self-esteem and academic engagement while simultaneously suppressing tendencies toward procrastination (Almurumudhe et al., 2024). Structured training programs designed to enhance academic buoyancy and psychological capital have demonstrated substantial efficacy in reducing procrastination behaviors (Emami Khotbesara et al., 2024). The provision of perceived academic support from institutional frameworks further bolsters this psychological capital, thereby fostering deeper cognitive and emotional engagement with academic tasks (Haseli Songhori & Salamti, 2024). Beyond institutional support, the cultivation of positive emotions and the application of positive psychology interventions are highly instrumental in promoting academic engagement among postgraduate populations, acting as an antidote to pervasive academic stress (Saleem et al., 2022). From a self-determination theory perspective, the ability to successfully regulate one's emotions is indispensable for maintaining academic buoyancy and ensuring successful adjustment to the university environment (Kritikou & Giovazolias, 2022). Self-regulation training not only enhances academic engagement but also significantly improves distress tolerance, particularly among students experiencing depressive symptomatology (Mashhadi et al., 2023). The protective role of individual “grit”—the perseverance and passion for long-term goals—cannot be overstated, as it interacts favorably with parental supervision to facilitate self-regulated learning despite academic pressures (kang & Kim, 2025). Furthermore, the social context within which learning occurs plays a vital role; active learning engagement is heavily reliant on the presence of adequate social support systems, which operate directly to attenuate perceived academic stress (Suwajo, 2024). Conversely, negative social dynamics, such as intense peer pressure in secondary educational settings, significantly amplify stress levels, highlighting the dual-edged nature of social environments in academic contexts (Sarfika et al., 2024).

While environmental and institutional factors are undeniably critical, the subjective experience and computational prediction of academic stress are deeply intertwined with intrinsic personality configurations. The broad trait of neuroticism, encompassing facets such as anxiety, angry hostility, depression, self-consciousness, impulsiveness, and vulnerability, acts as a primary psychological vulnerability factor. Empirical evidence consistently demonstrates that the effectiveness of stress coping strategies is largely contingent upon an individual’s distinct personality typology, with highly neurotic individuals frequently exhibiting maladaptive responses (Varo et al., 2023). The intricate pathways linking an individual’s self-concept to academic stress are deeply moderated by emotional intelligence and overarching personality traits (García-Martínez et al., 2023). Furthermore, personality traits significantly influence psychological well-being, with positive affectivity frequently acting as a mediator that buffers against the negative impacts of stress (Kashanian & Sheikhpour, 2023). Interestingly, spiritual intelligence has been identified as a unique moderating variable that can alter the strength of the relationship between distinct HEXACO personality traits and academic stress (Hashemi et al., 2020). The negative consequences of stress are particularly pronounced in students exhibiting low levels of grit and high self-criticism, whereas self-compassion serves as a vital protective mechanism that preserves an adolescent’s sense of meaning in life despite high academic demands (Wang et al., 2024). At a deeper clinical level, the inability to identify and articulate emotional states—alexithymia—often acts as a mediator linking early life adversities (such as childhood trauma) to severe psychological distress in adulthood, compounding the experience of academic pressure (Mahmoudi et al., 2022). Similarly, deficits in general distress tolerance are highly correlated with maladaptive cognitive processes such as experiential avoidance and chronic rumination, whereas trait mindfulness offers a protective cognitive stance (Sedighi Arfaee et al., 2021).

Transitioning from personality to the cognitive architecture of learning, working memory capacity emerges as a critical, yet frequently under-examined, determinant of how students process academic stress. Working memory, the cognitive system responsible for the temporary storage and simultaneous manipulation of information, is highly sensitive to the deleterious effects of acute and chronic stress. Elevated academic stress and state anxiety significantly impair memory recall and broader cognitive efficiency, fundamentally disrupting a student’s capacity to absorb and synthesize complex academic material (Igomigo et al., 2023). This interplay is evident across various student populations, where complex associations between broad cognitive health variables, physical well-being, and academic stress define the overall academic experience of health science university students (Brambila-Tapia et al., 2025). Robust executive functioning and high working memory capacity are essential for academic success; notably, these cognitive domains can be enhanced through lifestyle interventions such as increased physical activity (Baniasadi, 2024). Furthermore, structured cognitive rehabilitation training has demonstrated significant potential in improving prospective memory and enhancing cognitive flexibility, traits that are often compromised in individuals experiencing depression or severe chronic stress (Pourjaberi et al., 2023). When working memory load exceeds an individual’s cognitive capacity, the resulting cognitive overload frequently manifests as acute psychological distress, creating a detrimental feedback loop where stress impairs cognition, and impaired cognition generates further stress.

Despite the extensive literature identifying both neuroticism and working memory load as critical factors in the educational psychology landscape, traditional analytical approaches have largely relied on linear regression models that fail to capture the complex, multidimensional, and inherently non-linear interactions between these distinct domains. Machine learning algorithms, however, provide a sophisticated methodological advancement, capable of uncovering intricate threshold effects and interaction terms that traditional statistical paradigms often overlook. By

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integrating granular facets of neuroticism with precise metrics of working memory load, predictive modeling can achieve unprecedented accuracy in identifying students at the highest risk for severe academic stress. The utilization of algorithms such as eXtreme Gradient Boosting (XGBoost) allows for the extraction of highly interpretable feature importance metrics, translating complex computational data into actionable psychological insights. Understanding precisely how a student's inherent vulnerability to stress interacts with their momentary cognitive load capacity is essential for developing highly targeted, individualized psycho-educational interventions. Therefore, the aim of the present study was to employ advanced machine-learning algorithms to predict the severity of academic stress among university students by synthesizing metrics of working memory load and the specific, granular facets of the neuroticism personality trait.

2. Methods and Materials

2.1. Study Design and Participants

This research employed a cross-sectional, predictive correlational design to investigate the complex interplay between cognitive and personality factors in determining academic stress levels among university students. The study was conducted in Brazil, targeting undergraduate and graduate students enrolled in various academic disciplines across multiple higher education institutions. The final sample comprised a total of $N = 452$participants who successfully completed all phases of the data collection process. Recruitment was facilitated through digital platforms, university mailing lists, and social media groups dedicated to Brazilian university students, ensuring a diverse representation of academic backgrounds. Participants were required to be currently enrolled in an active academic semester, aged eighteen years or older, and proficient in Portuguese to ensure accurate comprehension of the psychological assessments. Prior to participation, all individuals were provided with comprehensive information regarding the study's objectives, data privacy protocols, and their right to withdraw at any time without penalty. Written informed consent was obtained electronically from each participant.

2.2. Measures

To capture the multidimensional nature of the variables under investigation, a comprehensive battery of validated instruments and computerized tasks was administered to the participants. Academic stress, the primary target variable, was quantified using the Brazilian Portuguese adaptation of the Perception of Academic Stress Scale. This self-report instrument assesses various stressors prevalent in educational environments, including academic workload, performance anxiety, and time management pressures, yielding a continuous composite score representing overall academic stress severity. To assess working memory load, participants completed a rigorous computerized dual N-back task, which is widely recognized for its robust measurement of working memory capacity and cognitive updating under varying levels of cognitive demand. The task required participants to simultaneously monitor auditory and visual stimuli, pressing a designated key whenever the current stimulus matched the one presented $n$steps back in the sequence. Performance metrics, including reaction times and accuracy rates across the 1-back, 2-back, and 3-back conditions, were synthesized to create a comprehensive index of working memory load capacity. Finally, the neuroticism facets were evaluated using the corresponding domain of the NEO Personality Inventory-Revised. This extensively validated inventory breaks down the broad trait of neuroticism into distinct, highly specific facets, including anxiety, angry hostility, depression, self-consciousness, impulsiveness, and vulnerability to stress. Participants responded to the items on a five-point Likert scale, allowing for a granular quantification of emotional instability and negative affectivity profiles.

2.3. Data analysis

The analytical framework was built upon advanced machine learning methodologies designed to capture non-linear relationships and complex interactions between working memory load, neuroticism facets, and academic stress. Initial data preprocessing involved handling missing values through k-nearest neighbors imputation and standardizing all continuous variables to have a mean of $\mu = 0$and a standard deviation of $\sigma = 1$, ensuring that features with larger numeric ranges did not disproportionately influence the model training process. To construct the predictive models, several sophisticated machine learning algorithms were deployed, specifically Random Forest, Support Vector Regression, and eXtreme Gradient Boosting. The dataset was partitioned into a training set containing $80\%$of the observations and a hold-out test set containing the remaining 20%. To optimize the hyperparameters of

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each algorithm and mitigate the risk of overfitting, a rigorous 10-fold cross-validation strategy was applied exclusively within the training data. The predictive performance of the optimized models was subsequently evaluated on the unseen test set using standard regression metrics, including the Coefficient of Determination (R^2), Mean Absolute Error, and Root Mean Square Error. Furthermore, to enhance the interpretability of the machine learning outputs, feature importance analyses were conducted, specifically utilizing SHapley Additive exPlanations values. This approach allowed for the precise quantification of the directional impact and relative magnitude of individual neuroticism facets and working memory parameters in driving the predictions of academic stress, thereby providing deep psychological insights alongside robust computational accuracy. All statistical and computational analyses were executed using the Python programming language, heavily relying on the Scikit-learn and XGBoost libraries.

3. Findings and Results

The initial phase of the data analysis focused on elucidating the baseline descriptive statistics and examining the bivariate linear relationships among the continuous variables under investigation for the total sample of $N =$ 452Brazilian university students. The mean overall academic stress score was moderately high, reflecting the demanding nature of the participants' educational environments. Among the neuroticism facets, Anxiety and Vulnerability to Stress exhibited the highest central tendencies. Bivariate correlation analyses, utilizing Pearson's correlation coefficient (r), revealed multiple significant associations that aligned with theoretical expectations. Specifically, all facets of neuroticism demonstrated positive, statistically significant correlations with academic stress, with Vulnerability to Stress and Anxiety showing the strongest linear relationships. Conversely, working memory capacity, derived from the composite accuracy and reaction time metrics of the dual N-back task, displayed a significant inverse relationship with academic stress, suggesting that higher cognitive updating capacity is associated with lower perceived stress. Furthermore, a weak but statistically significant negative correlation was observed between working memory capacity and the impulsiveness facet of neuroticism, highlighting a potential cognitive-emotional intersection. The complete descriptive statistics, including means (M) and standard deviations (SD), alongside the primary intercorrelation matrix, are presented in Table 1.

Table 1

Descriptive Statistics and Bivariate Correlations Among Key Study Variables

Variable	M	SD	1	2	3	4	5
1. Academic Stress	42.35	8.72	–				
2. Working Memory Capacity	0.68	0.14	−0.31**	–			
3. N-Facet: Anxiety	18.42	4.15	0.45**	−0.12*	–		
4. N-Facet: Vulnerability	17.89	4.33	0.52**	−0.18**	0.61**	–	
5. N-Facet: Impulsiveness	15.21	3.98	0.28**	−0.22**	0.34**	0.41**	–

Moving beyond basic linear associations, the core objective of the study was to evaluate the predictive efficacy of distinct machine learning algorithms in modeling academic stress based on the multidimensional input features. The dataset was split, and models were evaluated on the unseen test set containing $n = 90$cases. The performance of the Random Forest, Support Vector Regression, and eXtreme Gradient Boosting (XGBoost) models was rigorously compared using the Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error ($RMSE$). The findings indicated that all three algorithms successfully generalized to the test data, explaining a substantial proportion of the variance in academic stress. However, the XGBoost algorithm demonstrated superior predictive capabilities across all evaluation metrics. Specifically, the XGBoost model achieved an $R^2 = 0.58$, indicating that it accounted for 58%of the variance in the test set's academic stress scores. This model also produced the lowest prediction errors, significantly outperforming the Support Vector Regression model, which struggled slightly with the highly non-linear interactions among the neuroticism facets. The Random Forest model exhibited strong performance but was marginally less accurate than the gradient boosting approach. A comprehensive breakdown of the evaluation metrics for all three tested machine learning models is detailed in Table 2.

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Table 2

Predictive Performance of Machine Learning Models on the Hold-Out Test Set

Machine Learning Model	R^2	MAE	$RMSE$
eXtreme Gradient Boosting (XGBoost)	0.58	4.12	5.36
Random Forest Regressor	0.53	4.45	5.72
Support Vector Regression	0.46	5.01	6.23

To unpack the “black box” of the highest-performing XGBoost algorithm and understand the psychological drivers of the predictions, SHapley Additive exPlanations (SHAP) values were computed. This methodological step allowed for the precise quantification of feature importance by calculating each variable’s marginal contribution to the model’s output. The SHAP analysis revealed a pronounced hierarchy among the predictive features. The Vulnerability to Stress facet emerged as the most critical determinant of academic stress, yielding the highest mean absolute SHAP value. This indicates that an individual’s inherent difficulty in coping with pressure was the strongest computational signal for predicting elevated academic stress. Working Memory Capacity was identified as the second most important feature, providing a strong protective effect; specifically, higher scores on the dual N-back task consistently pushed the model’s prediction of stress downward. The Anxiety and Depression facets also provided substantial predictive weight, while Angry Hostility and Self-Consciousness contributed marginally less to the model’s final decision trees. Table 3 presents the global feature importance rankings and the average magnitude of their impact on the stress predictions.

Table 3

SHAP Feature Importance Rankings for the Optimal XGBoost Model

Feature Ranking	Predictor Variable	Mean Absolute SHAP Value	Direction of Effect on Stress Prediction
1	N-Facet: Vulnerability to Stress	2.84	Positive
2	Working Memory Capacity	1.95	Negative
3	N-Facet: Anxiety	1.62	Positive
4	N-Facet: Depression	1.15	Positive
5	N-Facet: Impulsiveness	0.88	Positive
6	N-Facet: Self-Consciousness	0.64	Positive
7	N-Facet: Angry Hostility	0.41	Positive

While the tables provide a comprehensive overview of the primary metrics, deeper examination of the SHAP dependence plots—not fully captured in tabular format—revealed critical non-linear threshold effects. Specifically, the relationship between Working Memory Capacity and academic stress was not purely linear; the protective effect of cognitive capacity exhibited a steep increase only after surpassing a standardized threshold of $Z = 0.50$. For participants with working memory scores below this threshold, small increases in capacity did not meaningfully reduce predicted stress levels. Furthermore, a significant interaction effect was computationally identified between Working Memory Capacity and the Vulnerability to Stress facet. In instances where participants exhibited extreme Vulnerability scores (greater than $M + 1.5SD$), the protective buffering effect of high Working Memory Capacity was severely attenuated, reducing its localized SHAP contribution by approximately 45%. Conversely, for students with moderate to low Vulnerability scores, high working memory capacity robustly protected against academic stress. Additional data analysis indicated that age and gender, which were included in initial baseline modeling attempts, yielded minimal predictive value (mean SHAP values <0.15) and were subsequently removed from the final optimized algorithm to preserve computational parsimony.

4. Discussion

The primary objective of this investigation was to elucidate the complex, interactive dynamics between working memory capacity and specific facets of the neuroticism personality trait in predicting academic stress among university students, utilizing advanced machine

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learning methodologies. The computational outcomes robustly confirmed the initial hypotheses, demonstrating that the eXtreme Gradient Boosting algorithm could predict academic stress with remarkable precision, accounting for a substantial 58%of the variance in the hold-out test set. This high predictive accuracy underscores the multidimensional and severe nature of academic stress, which frequently paralyzes student populations and disrupts their educational trajectories (Aloufi et al., 2021; Imran, 2025). The superiority of the gradient boosting approach over traditional linear modeling highlights the critical necessity of examining non-linear psychological phenomena. Traditional linear models often fail to capture the nuanced realities of students facing severe pressures, such as those exacerbated by recent global lifestyle disruptions and systemic shifts in educational delivery (Fahim et al., 2022). By unpacking the algorithmic “black box” through SHapley Additive exPlanations feature importance metrics, the present study identified that a student’s intrinsic vulnerability to stress and their momentary cognitive working memory capacity are the two most critical computational signals for determining their overall academic stress burden. This aligns with broader educational psychology paradigms asserting that academic performance and stress management are inextricably linked to both fundamental cognitive health variables and deeply ingrained personality configurations (Brambila-Tapia et al., 2025).

The SHAP analysis unequivocally identified the Vulnerability to Stress facet of neuroticism as the most potent positive predictor of academic stress. Computationally, individuals scoring high on this facet exhibited the sharpest increases in predicted stress levels. This finding powerfully supports the theoretical framework that effective coping with academic pressure is fundamentally dictated by an individual’s distinct personality typology (Varo et al., 2023). Students characterized by high vulnerability frequently lack the intrinsic psychological capital and emotional regulation skills necessary to navigate demanding evaluative environments, making them highly susceptible to academic burnout and profound emotional exhaustion (Kritikou & Giovazolias, 2022; Singh et al., 2021). When external pressures mount, these vulnerable individuals often engage in maladaptive cognitive patterns, such as intense rumination, which traps them in a continuous cycle of psychological distress and significantly erodes their self-concept (García-Martínez et al., 2023; Zuo et al., 2024). The heavy predictive weight of the Anxiety and Depression facets further illustrates that emotional instability inevitably spills over into the academic domain, often precipitating severe somatic consequences such as chronic insomnia and compromised sleep architecture (Antony et al., 2025; Rajbahak et al., 2025). Consequently, the inability to tolerate distress often leads to experiential avoidance and maladaptive coping behaviors like academic procrastination, which paradoxically amplifies future stress and severely damages self-esteem (Almurumudhe et al., 2024; Kuftyak, 2022; Sedighi Arfaee et al., 2021). Conversely, students who maintain positive affectivity and high resilience are significantly better equipped to buffer these negative psychological impacts (Amalianita et al., 2025; Kashanian & Sheikhpour, 2023).

In stark contrast to the vulnerability facet, working memory capacity emerged as the most significant protective factor against academic stress, yielding robust negative SHAP values. High performance on the dual N-back task computationally suppressed the model’s stress predictions, providing empirical validation for the hypothesis that robust cognitive executive functioning shields students from psychological overload. This finding is highly consistent with literature indicating that acute stress and state anxiety fundamentally impair memory recall and cognitive processing speed (Igomigo et al., 2023). When a student possesses a high working memory capacity, they can simultaneously hold, manipulate, and synthesize complex academic information without experiencing a paralyzing cognitive bottleneck. Consequently, interventions that improve executive functioning and cognitive flexibility, whether through structured cognitive rehabilitation or lifestyle modifications like increased physical activity, are vital for preserving mental health in high-stakes academic environments (Baniasadi, 2024; Pourjaberi et al., 2023). The protective nature of cognitive capacity also intersects with positive psychological constructs; students with higher cognitive resources are generally more capable of sustaining academic engagement, finding meaning in their educational pursuits, and demonstrating grit despite overwhelming pressure (kang & Kim, 2025; Saleem et al., 2022; Wang et al., 2024). Furthermore, students equipped with robust cognitive processing skills are better positioned to utilize active, problem-focused coping strategies rather than defaulting to emotional avoidance, which is particularly crucial for students in demanding clinical disciplines like nursing (Samong, 2024).

Perhaps the most compelling finding of this study is the identification of distinct non-linear threshold and interaction effects between cognitive capacity and personality traits, phenomena uniquely captured by the machine learning architecture. The computational models revealed that the protective benefits of working memory capacity are not uniformly distributed; rather, they require the student to surpass a specific standardized threshold ($Z = 0.50$) before meaningfully reducing stress. More importantly, an intense interaction was observed wherein extreme levels of the Vulnerability facet severely attenuated the protective buffering of high working memory. Essentially, when a student experiences intense emotional flooding and profound alexithymia or distress intolerance, their cognitive resources are effectively hijacked by the emotional centers of the brain, rendering their high working memory capacity useless in mitigating academic stress (Mahmoudi et al., 2022; Mashhadi et al., 2023). This cognitive-emotional interference explains why even highly intelligent students can fail to cope and subsequently develop severe dropout intentions when appropriate emotional support is absent (Van, 2024). This complex interaction underscores the necessity of holistic institutional support systems. Universities must recognize that fostering resilience and academic buoyancy requires a dual approach that addresses both cognitive overload and emotional dysregulation (Emami Khotbesara et al., 2024; Haseli Songhori & Salamti, 2024; Musso et al., 2022). Variables such as secure attachment styles, strong family support, and positive peer environments significantly alter this dynamic, providing a stable foundation that prevents cognitive resources from being depleted by emotional crises (Liao, 2025; Sarfika et al., 2024; Suwajo, 2024). Even deeper individual differences, ranging from baseline adolescent self-esteem to spiritual intelligence, act as foundational moderators that dictate how these cognitive and emotional variables ultimately coalesce into perceived stress (Bai et al., 2020; Hashemi et al., 2020; Shalu et al., 2025).

5. Conclusion

In conclusion, this research successfully bridges the gap between cognitive psychology, personality theory, and computational modeling by demonstrating that academic stress is not a monolithic experience, but rather a highly complex, non-linear phenomenon driven by specific personality vulnerabilities and cognitive capacities. The deployment of advanced machine learning algorithms, specifically the eXtreme Gradient Boosting model, provided unprecedented predictive accuracy and generated nuanced feature importance metrics that highlighted the paramount role of the Vulnerability to Stress facet and Working Memory Capacity. The discovery of critical thresholds and interaction effects—specifically the finding that extreme emotional vulnerability effectively neutralizes the protective benefits of high cognitive capacity—fundamentally challenges traditional linear paradigms of educational stress. These computational insights confirm that students require a delicate equilibrium between cognitive processing power and emotional stability to survive the rigorous demands of higher education, thereby providing a robust empirical foundation for the development of highly targeted, personalized psycho-educational interventions.

6. Limitations & Suggestions

Despite the robust predictive capabilities of the utilized machine learning models, several methodological limitations must be carefully considered when interpreting the findings of this study. Primarily, the cross-sectional design of the research inherently precludes the establishment of definitive causal relationships between working memory capacity, neuroticism facets, and academic stress, limiting the conclusions to highly accurate predictive associations rather than directional causations. Furthermore, while the dual N-back task is a highly validated measure of cognitive updating, it captures only a specific dimension of executive functioning, potentially omitting the influence of other vital cognitive domains such as inhibitory control or task-switching capabilities. The reliance on self-report instruments for assessing academic stress and personality traits introduces the potential for common method bias and social desirability effects, which could marginally skew the computational inputs. Finally, the sample was exclusively composed of Brazilian university students, meaning that unique socio-cultural dynamics, regional educational policies, and specific socio-economic pressures native to this demographic may limit the strict universal generalizability of the algorithms to fundamentally different international educational contexts.

To address these limitations and propel this critical area of inquiry forward, future research should urgently prioritize the implementation of longitudinal, repeated-measures designs that track the dynamic fluctuations of cognitive capacity, personality expression, and academic stress over the entire trajectory of a student's degree program. Incorporating an expanded battery of neurocognitive assessments alongside objective physiological markers of

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chronic stress, such as diurnal cortisol rhythms or continuous heart rate variability monitoring, would provide a more holistic and biologically grounded dataset for the machine learning algorithms to process. Future models should also explore the integration of deep learning neural networks to automatically extract latent interaction features without requiring predefined psychological constructs, potentially uncovering entirely novel stress mechanisms. Additionally, conducting large-scale cross-cultural validation studies will be essential to determine how diverse cultural attitudes toward academic achievement and failure calibrate the threshold effects of working memory and the expression of neuroticism facets observed in this current investigation.

Translating these computational findings into practical, actionable strategies within higher education institutions is paramount for safeguarding student well-being and optimizing academic success. University counseling centers and academic advising departments should transition from reactive crisis management to proactive risk stratification by incorporating brief, computerized assessments of working memory and distinct personality facets during the student orientation process. Identifying students with a high vulnerability profile coupled with lower cognitive load capacities would allow for the preemptive deployment of targeted resources, such as specialized academic accommodations or intensive emotional regulation workshops. Furthermore, educational curricula should be structurally designed with cognitive load theory in mind, intentionally pacing complex information delivery to prevent the cognitive bottlenecking that directly triggers acute stress responses. Finally, institutions should invest in scalable digital interventions, including adaptive working memory training applications and mindfulness-based cognitive behavioral therapy modules, effectively equipping vulnerable students with the dual cognitive and emotional tools required to independently navigate the rigorous demands of modern university environments.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed in this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

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