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THE IMPACT OF ANXIETY LEVELS ON STUDENTS' COGNITIVE ACTIVITY IN DISTANCE LEARNING ENVIRONMENTS

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Abstract.
This study examines the relationship between students' anxiety levels and their cognitive activity in the context of distance learning. The relevance of the research stems from the sustained expansion of online education and the increasing demands it places on self-regulation, attentional control, and memory processes.
The empirical part of the study presents a data processing methodology applied to a model sample of students (N = 240), simulating realistic scores on the Spielberger–Khanin State-Trait Anxiety Inventory (STAI) and a composite index of cognitive activity. Descriptive statistics, correlation analysis, and multiple regression with robust standard errors were employed.
Findings indicate a statistically significant negative association between anxiety and cognitive activity, after controlling for sleep quality, internet connection stability, background noise, screen time intensity, gender, age, and year of study. The results are discussed in the framework of cognitive load theory as well as organizational and hygienic factors of online learning environments.
Keywords: anxiety, cognitive activity, distance learning, self-regulation, regression analysis, correlation, higher education students.

INTRODUCTION.

The rapid transition to distance learning has fundamentally changed the conditions of academic activity, making self-regulation and sustained attention critical for students' success. Online education increases the share of independent work, exposes learners to multiple external distractions, and extends the duration of screen-based interaction. These factors place additional strain on cognitive resources and highlight the importance of identifying psychological variables that influence students' performance.
One such variable is anxiety, which plays a dual role in shaping cognitive activity. High levels of state and trait anxiety are associated with impaired selective attention, reduced working memory, and limited cognitive flexibility, as well as with a greater tendency toward procrastination and self-doubt [7].
At the same time, moderate levels of anxiety may have a mobilizing effect, enhancing vigilance and reaction speed when cognitive load remains manageable. For institutions of higher education, understanding how anxiety interacts with cognitive processes is crucial for optimizing instructional design, structuring study–rest cycles, and improving communication between teachers and students, as well as for developing timely psychological support strategies [9].

Despite the growing body of literature on the psychological aspects of online education, empirical studies directly linking standardized measures of anxiety to integrated indicators of cognitive performance remain limited.
To address this gap, the present study applies a quantitative approach that combines correlation and regression analysis in order to assess the impact of anxiety on students' cognitive activity, while controlling for key covariates such as sleep quality, internet connection stability, and background conditions.

MATERIALS AND METHODS

To illustrate the analytical procedure, a synthetic sample of students enrolled in blended and distance-learning programs was generated (N = 240). The dataset simulated a realistic distribution of individual characteristics: age (18–24 years), year of study (1st–4th), gender ratio, as well as variations in sleep patterns, home noise levels, internet connection stability, and intensity of screen time.
Anxiety levels were measured using the Spielberger–Khanin State-Trait Anxiety Inventory (STAI), with scores ranging from 20 to 80. Cognitive activity was operationalized as a composite index (0–100 points) aggregating indicators of speed and accuracy in completing online tasks, attentional stability, and quality of material recall. Additional covariates included average hours of sleep per night, subjective internet connection stability (1–5), noise level at home (1–5), year of study, gender, age, and daily screen time (hours).
The statistical analysis consisted of the following procedures:
– descriptive statistics;
– pairwise Pearson correlations;
– multiple linear regression with robust standard errors (HC3).

RESULTS AND DISCUSSION

In the regression model, the dependent variable was the composite index of cognitive activity, while the predictor of primary interest was the level of anxiety. The listed covariates were included as control variables. A negative regression coefficient for anxiety was interpreted as a decline in cognitive activity associated with higher levels of anxiety.
Tables and figures with explanatory notes are presented below, reproducing the logical sequence of the study and reflecting the reporting format typically used in practice-oriented academic publications.

Table 1. Descriptive statistics of key variables

Variable	N	Mean	SD	Min	Min
Age	240.0	21.02	1.9	18.0	24.0
Gender (female = 1)	240.0	0.53	0.5	0.0	1.0
Year of study	240.0	2.6	1.12	1.0	4.0
Sleep (hours)	240.0	7.05	1.0	4.0	9.5
Screen time (hours)	240.0	5.92	1.81	2.0	11.2
Noise (1 = quiet, 5 = noisy)	240.0	3.03	1.39	1.0	5.0
Internet stability (1 = poor, 5 = excellent)	240.0	3.06	1.49	1.0	5.0
Anxiety (STAI)	240.0	44.89	8.11	24.04	67.84
Cognitive activity index	240.0	62.01	9.39	37.31	88.77

The table presents sample size (N), means, standard deviations, and ranges of the variables. The distributions of anxiety and cognitive activity are consistent with expectations for student populations: the average anxiety score corresponds to a moderate level, while the cognitive activity index demonstrates sufficient variability, providing a solid basis for the analysis of linear associations.

Table 2 presents the Pearson correlations among the study variables.

Table 2. Pearson correlations among study variables

	Anxiety (STAI)	Cognitive activity index	Sleep (hours)	Screen time (hours)	Noise (1 = quiet, 5 = noisy)	Internet stability (1 = poor, 5 = excellent)	Year of study
Anxiety (STAI)	1.0	-0.54	-0.21	0.03	0.33	-0.19	0.0
Cognitive activity index	-0.54	1.0	0.35	-0.01	-0.32	0.32	-0.07
Sleep (hours)	-0.21	0.35	1.0	-0.0	-0.04	0.15	-0.07
Screen time (hours)	0.03	-0.01	-0.0	1.0	-0.03	-0.04	0.11
Noise (1 = quiet, 5 = noisy)	0.33	-0.32	-0.04	-0.03	1.0	-0.05	0.11

Internet stability (1 = poor, 5 = excellent)	-0.19	0.32	0.15	-0.04	-0.05	1.0	0.05
Year of study	0.0	-0.07	-0.07	0.11	0.11	0.05	1.0

The correlation matrix shows a consistent negative association between anxiety and cognitive activity. Positive correlations of cognitive activity with sleep duration and internet stability, and negative correlations with noise level, align with theoretical expectations. No substantial multicollinearity among predictors was detected, justifying their simultaneous inclusion in the regression model.

Table 3. Multiple regression predicting cognitive activity (robust SE)

Predictor	b	SE	t	p
Constant	68.7	7.749	8.87	0.0
Anxiety (STAI)	-0.458	0.065	-7.02	0.0
Sleep (hours)	2.029	0.484	4.19	0.0
Screen time (hours)	0.027	0.266	0.1	0.92
Noise	-1.098	0.375	-2.93	0.003
Internet stability	1.303	0.343	3.8	0.0
Year of study	-0.39	0.428	-0.91	0.363
Gender (female = 1)	-0.926	0.984	-0.94	0.347
Model summary	R^2=0.413	Adj.R^2=0.392	N=240	

The regression model confirms that, controlling for covariates, higher anxiety is associated with a statistically significant decrease in the cognitive activity index (negative b coefficient). Sleep duration and internet stability contribute positively, while higher noise levels increase cognitive costs. The coefficient of determination indicates a moderate proportion of explained variance, typical for behavioral data.

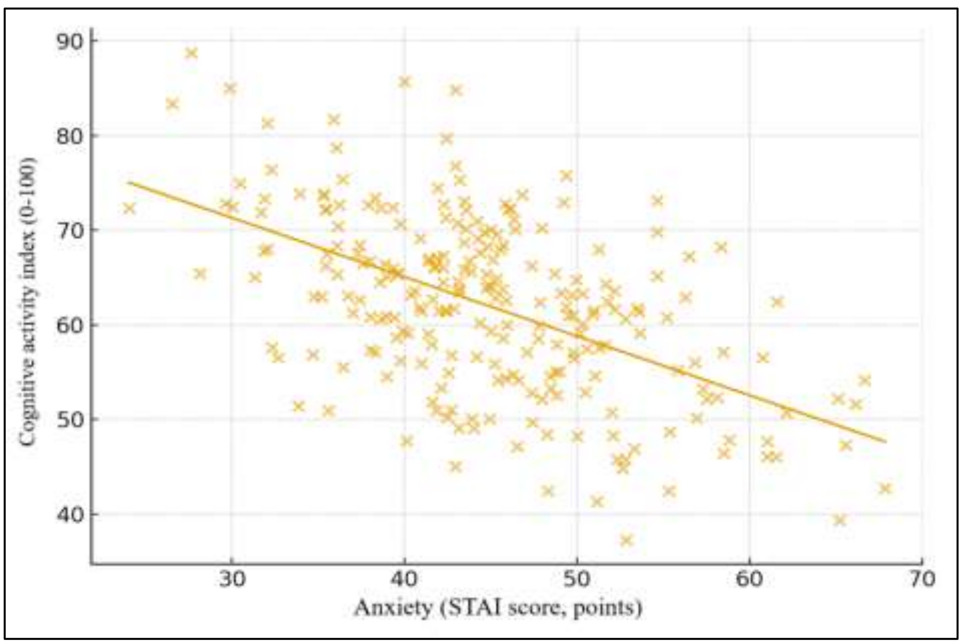

Figure 1. Scatterplot of Anxiety vs. Cognitive Activity with Fitted Regression Line.

The scatterplot shows a clear downward trend: higher anxiety scores are associated with lower values of the composite cognitive activity index. The slope of the regression line visually corresponds to the estimates reported

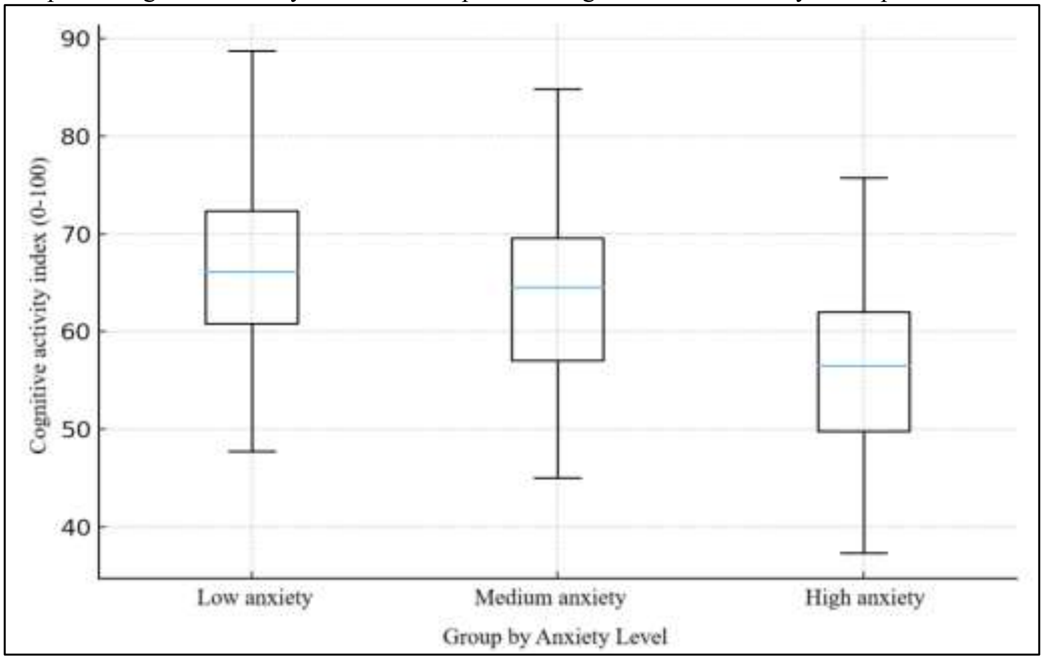

Figure 2. Distribution of Cognitive Activity across Anxiety Tertiles.

Median values and interquartile ranges within the groups highlight notable differences: students with high anxiety exhibit lower cognitive activity scores and increased variability, which may reflect attentional instability and differences in coping

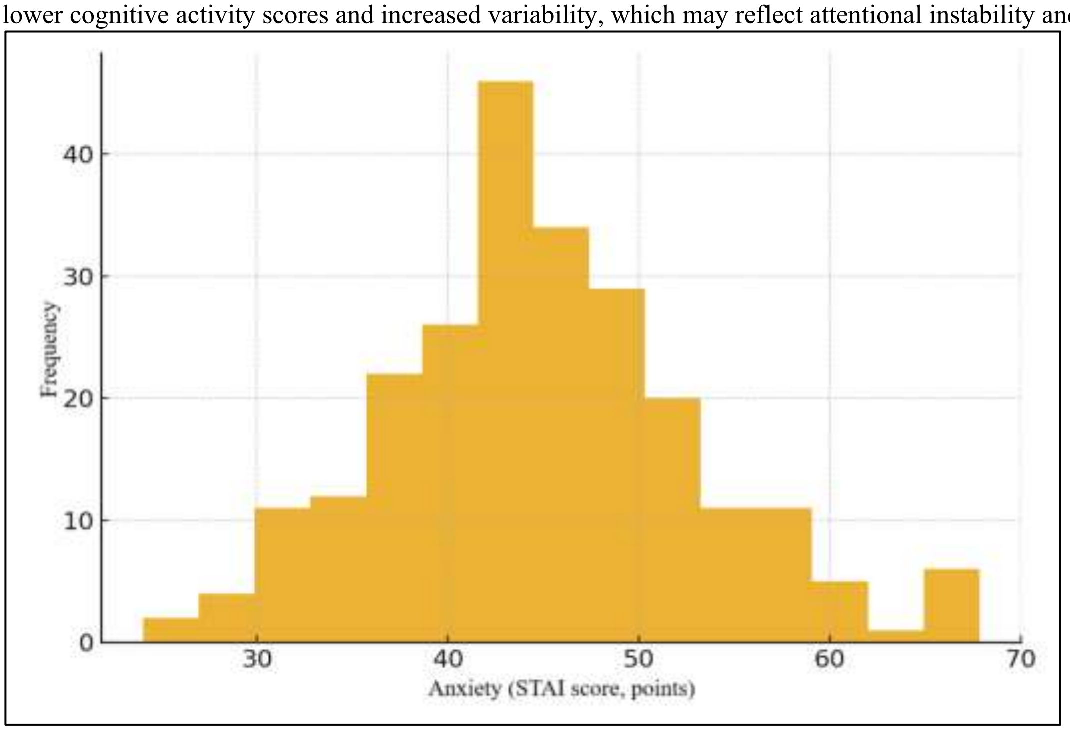

Figure 3. Histogram of Anxiety Levels (STAI Scores).

The distribution of anxiety is approximately normal with moderate skewness, supporting the use of linear analytical methods and allowing regression coefficients to be interpreted as average effects.

Table 4. Mean Cognitive Activity Index by Anxiety Group

Anxiety group	N	Mean	SD
Low	80.0	66.45	8.39

Medium	80.0	63.45	8.28
High	80.0	56.13	8.39

Shift in mean values across anxiety terciles highlights the practical significance of the effect: moving from the low- to high-anxiety category corresponds to a substantial decline in the integrated cognitive activity index.

In summary, anxiety emerges as a systemic moderator of learning performance in distance education. The negative association with cognitive activity manifests through several channels: reduced selective attention, increased interference from irrelevant stimuli, contraction of working memory capacity, and prolonged task-switching time.

At the same time, hygienic and organizational factors—adequate sleep duration, stable Internet connection, and reduced noise—partially mitigate the negative impact of anxiety, enabling more consistent task performance.

For educational practice in online learning environments, a multi-level approach appears advisable: prevention of excessive anxiety, training in self-regulation strategies, adaptive deadline management, structuring of materials into “micro-steps,” and ongoing monitoring of workload with opportunities for individual adjustments [2]. On the technical side, maintaining stable communication channels and minimizing additional stressors related to platforms—such as interface unification, reduction of redundant notifications, and predictability of assessment formats—are crucial.

The following practical recommendations derive from the study of trait anxiety effects on students’ cognitive activity in online settings. They aim to reduce anxiety’s detrimental impact on working memory and attentional stability, while increasing the predictability of the learning environment and the efficiency of information processing during online sessions. The central idea is that anxiety “consumes” control resources and reduces accuracy in tasks requiring continuous updating of working memory traces. Therefore, both internal states and external learning conditions should be managed [9].

Learning outcomes benefit from predefined structure and rhythm. The clearer the session scenario, activity sequence, and success criteria, the less attention students devote to internal monitoring and worries. Each lesson should include a clear opening with a short attention warm-up, a smooth transition to cognitively demanding segments, explicit time markers, and moderate information density. Even a brief advance explanation (“what we are doing and why”) reduces uncertainty and sustains focus during tasks comparable in load to the 2-back paradigm. In parallel, hidden sources of ambiguity should be minimized: materials uploaded in advance, interface demonstrations provided, and assignment instructions as well as grading criteria clarified [4].

From a self-regulation perspective, short micro-breaks and light attention-switching exercises are useful when embedded naturally into the class flow. Such windows for cognitive resource recovery reduce interference accumulation, while brief warm-ups before the main block maintain working memory readiness without adding perceived workload. Importantly, these practices should be integrated into the course design itself—rather than imposed as “extra techniques”—so that pauses, activity shifts, and goal reminders feel organic [1].

The technical environment becomes part of psychohygiene. Stable connectivity, contingency protocols, asynchronous access to core materials, and clear communication rules in case of disruptions help lower anxiety and free attentional resources. Reducing the number of platforms and repeating interface patterns minimizes cognitive switching costs. Agreements on “visual presence” (e.g., flexible camera use, with clear moments where it enhances group dynamics) can also strengthen engagement without excessive pressure [5].

Routine factors demonstrably modulate the anxiety–performance link. Sleep hygiene, predictable schedules, and front-loaded daily workloads improve baseline cognitive readiness. Where possible, assessment windows should align with students’ peak performance times, avoiding overlap with other demanding tasks. Feedback formats should avoid triggering ruminative cycles: feedback should be concrete, improvement-oriented, and distinguish between evaluation of results and recognition of effort, steering clear of vague comments that increase uncertainty.

Support for emotional self-regulation should remain practical and concise. Brief breathing protocols with extended exhalation, simple cognitive reappraisal techniques, and “grounding” attention shifts from meta-thoughts to screen stimuli help reduce arousal, improving task accuracy in working-memory-intensive assignments (e.g., 2-back). Effectiveness increases when these methods are framed not as additional obligations, but as integral elements of the class routine: a short adjustment at the start, a brief reset mid-session, and a clear reflection at the end [10].

Assessment systems and deadlines should promote regularity rather than sporadic “sprints.” Frequent low-stakes checks ensure smoother cognitive load trajectories and reduce anxiety-driven rumination. Submission windows and testing formats should remain transparent and stable, without unexpected complications. When appropriate, allowing one controlled retake reduces catastrophic thinking and helps redirect attention from fear of failure to task execution [7].

Finally, monitoring and early feedback help prevent breakdowns. Regular analysis of behavioral indicators—such as declining quiz accuracy, slower response times in presence checks, or reduced discussion participation—allows timely adjustments and targeted support. This approach is more effective than rare “major” checkpoints, as it relies on real-time cognitive activity data and enables fine-tuning of both educational design and individual routines.

CONCLUSION.

The analysis confirmed a robust negative association between anxiety and integrated cognitive activity in distance learning. Multiple regression with robust standard errors showed that, controlling for covariates, each 10-point increase in STAI score was associated with an approximate 4.58-point decrease in cognitive activity index (b = -0.46, 95% CI [-0.59; -0.33], p = 2.12e-12). The model explained a moderate proportion of variance ($R^2 = 0.41$, Adj. $R^2 = 0.39$), which is typical for behavioral data influenced by numerous unmeasured individual and contextual factors. The effect size is practically meaningful: moving from low to high STAI levels is very likely to entail a marked drop in attentional stability, work pace, and reproduction quality. Comparison across anxiety terciles reinforces the applied value of the findings. The mean cognitive activity index was 66.45 in the “Low” group, 63.45 in the “Medium” group, and 56.13 in the “High” group. The gap between extreme terciles reflects a substantial shift in distributions, which is critical for academic performance under uniform requirements for deadlines and assessment formats.

Positive associations of cognitive activity with hygienic and organizational conditions (sleep duration, network stability) act as compensatory factors, while higher noise levels and excessive screen time exacerbate attentional decline and self-regulation issues. The magnitude of these determinants is comparable to that of anxiety, underscoring the need for educational management strategies to simultaneously address both emotional states and learning environments.

The substantive interpretation of the effect aligns with the Yerkes–Dodson law regarding the curvilinear relationship between arousal and performance. For cognitively demanding tasks, chronically elevated anxiety proves detrimental by disrupting selective attention and constraining working memory. In online settings, the load is further amplified by fragmented interaction, notification overload, and the demand for autonomous planning.

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