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Influence of digital educational platforms on cognitive development and emotional well-being

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ABSTRACT

This study aimed to identify psychophysiological markers that shape students' cognitive–emotional trajectories during learning with Moodle 3.9, supplemented by Canvas learning management system (LMS) for video delivery and Kahoot for game-based assessments. The experiment involved 124 undergraduate students and spanned 16 weeks with five measurement points: the experimental group studied using digital platforms, while the control group followed a traditional format. The methodology incorporated Raven's, Stroop, and N-back cognitive tests; measurements of heart rate, skin conductance, and cortisol levels; facial expression analysis; and learning-platform data. Working memory improved by 2.2 points with an effect size of d=2.14, and Stroop interference decreased by 36 milliseconds. The physiological cost included a reduction in heart-rate variability (root mean square of successive differences or RMSSD) from 42±12 to 28±8 ms and a two-hour shift in daily cortisol rhythms. Cluster analysis revealed three behavioral profiles. The strategic group scored 8.7 out of 10 while completing 40% of the material. Predictive models identified academic failure with 82.3% accuracy 21 days in advance, showing 76% sensitivity and 81% specificity. Individualized interventions triggered by physiological indicators increased academic performance by 24% and reduced stress by 38%. The return on investment was 4.2 to 1. The findings support the integration of early-warning algorithms into educational systems.

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1. INTRODUCTION

Educational institutions are undergoing a paradigm shift, as digital platforms increasingly reshape learners' cognitive engagement and emotional states [1]. The transition from examination-centered systems to technology-mediated instruction is transforming pedagogical practices and reorganizing underlying cognitive and affective processes. Information overload arises from the simultaneous processing of multiple content formats, including video, text, and audio [2]. Digital fatigue now affects 67% of students; sustained screen exposure depletes attentional resources and impairs memory retention [3]. A paradox emerges access to information expands, while the depth of comprehension declines [4]. Some students struggle to maintain prolonged concentration during video lectures [5]. Learning self-regulation is disrupted by constant notifications, chats, and interface elements that compete for attention [6].

Emotional isolation further heightens cognitive strain. Limited face-to-face interaction with instructors reduces empathy and increases student anxiety [7]. Continuous performance monitoring by learning analytics systems induces stress levels comparable to those caused by high-stakes examinations [8]. The brain undergoes measurable reorganization when interacting with digital interfaces [9]. Linear, sustained reading is increasingly replaced by fragmented text scanning, and hyperlink navigation cultivates rapid task switching at the expense of prolonged concentration. The prefrontal cortex adapts to the continuous processing of notifications, deadlines, and video content – each informational stream drawing on the same limited attentional-control resources [10]. Neural pathways supporting superficial processing are formed more quickly, while mechanisms responsible for deep learning become attenuated.

The emotional consequences extend beyond temporary discomfort. Reduced instructor presence diminishes empathy, and students who rely on automated feedback exhibit weaker emotional self-regulation than those receiving human-mediated support [11]. Algorithmic monitoring intensifies test anxiety by tracking every click, submission timestamp, and engagement pattern – forms of pressure largely absent in traditional classroom settings [12]. Gamification produces mixed outcomes: the initial spike in motivation is often followed by habituation, after which external rewards lose their effectiveness [13].

Scientific models describing these processes remain fragmented. Cognitive load theory offers tools for optimizing working memory but largely overlooks affective dimensions [14]. Research on emotional well-being emphasizes stress and sense of belonging while neglecting indicators of cognitive engagement. There is a notable absence of integrative frameworks that link physiological markers of stress with the quality of information processing [15]. Learning analytics generates extensive datasets, yet predictive models tend to prioritize academic outcomes, overlooking holistic learner development [16].

Methodological gaps persist across all measurement approaches. Self-report instruments capture subjective experiences but are prone to bias. Physiological monitoring yields objective data but requires costly equipment [17]. Longitudinal studies examining cognitive–emotional dynamics are limited; most provide cross-sectional snapshots rather than developmental trajectories over time [18]. Cross-cultural variation remains insufficiently explored. Learners in collectivist contexts typically require greater social interaction and group-based learning than their peers in individualist cultures [19].

2. LITERATURE REVIEW

Cognitive load theory in digital learning environments reveals fundamental tensions in optimizing working memory. Extraneous load components differ in both origin and measurement, and aggregating them obscures distinctions that are critical for instructional design [2]. Dual coding operates inconsistently across contexts. Multimodal instruction outperforms text-only formats for vocabulary with strong visual representations, yet these advantages disappear when animations are accompanied by excessive captions [20]. Segmentation likewise yields mixed results: pauses improve learning in physiology courses ($p=0.048$), whereas eye-tracking guidance can reduce performance among advanced learners due to redundancy effects [21]. Evidence-based design principles produce moderate to large effects on memory when applied individually, but boundary conditions diminish their benefits for prepared students, generating a reverse expertise effect [22].

The relationship between anxiety and self-efficacy is similarly inconsistent. Contrary to theoretical expectations, self-efficacy and anxiety in online learning show a positive correlation. Students with higher confidence experience greater tension as their confidence increases [23]. Readiness does not predict anxiety levels; well-prepared learners studying from home report comparable stress levels [24]. Physiological markers of stress are interpreted inconsistently. Heart rate variability (HRV) is linked to negative affect due to reduced parasympathetic activity, yet the relationship between HRV components and autonomic regulation is nonlinear [25]. Brief biofeedback interventions lower perceived stress and produce statistically significant physiological changes [26]. However, acute stress shows minimal variation, suggesting a sustained rather than transient effect [27].

Emotional labor in online settings deviates from expectations. Remote instruction reduces surface acting compared to face-to-face formats, while introducing new pressures related to managing cameras and chat interactions [28]. Cultural groups differ in emotion regulation strategies: Asian learners tend to suppress and avoid emotion, whereas Western learners rely more on cognitive reappraisal. These differences complicate the development of universal methodological approaches [29].

Activation of the brain's default mode network (DMN) cannot be reduced to a simple task–negative pattern. Weak task synchronization appears across cognitive assessments, and both activation and deactivation shift unpredictably, indicating a nonlinear relationship between internal processing and external task demands [30]. Intracranial recordings show coherent low-frequency activity during rest and task-modulated changes during episodic encoding. Subcomponents activate sequentially according to memory demands rather than undergoing uniform suppression [31].

Neural mechanisms of loneliness reveal coordinated changes across cortical and limbic regions, though dose–response relationships remain undetermined [32]. Short-term isolation sharpens motivation for social contact through a midbrain hunger-like mechanism ($t(36)=23.90$, $p<0.001$), whereas prolonged isolation differs qualitatively from brief deprivation [33]. Prefrontal activation during multitasking depends on the structure of attentional demands. Discrete-task requirements generate interference patterns distinct from those elicited by continuous tasks, even when task duration is held constant [34]. Portable functional near-infrared spectroscopy (fNIRS) captures load fluctuations through increases in oxygenated hemoglobin during multitasking, although dual-channel recordings restrict the spatial precision of inferences [35].

Learning-analytics-based interventions yield significant improvements. Automated behavioral prompts outperform generic reminders [36]. However, accurate predictions do not translate into improved outcomes unless they are translated into actionable steps. Four parameters are central: data types, analytical methods, objectives, and stakeholder needs. Alignment between indicators and feedback remains weak. Clickstream models illuminate behavioral patterns. Cyclical viewing with pauses predicts high performance, linear viewing produces modest gains, and playback speeds above 1.25× without pauses reduce learning outcomes [37]. Markov models identify latent states – exploration, practice, and assessment – whose occupancy explains performance variability when transition probabilities are considered [38].

The practical implementation of privacy often diverges from stated policy. Technical safeguards such as encryption and de-identification receive primary attention, whereas organizational data-copying procedures expand exposure risks [39]. Model objectives may shift as systems move from measuring engagement to supporting high-stakes decisions without renewed validation [40]. Individual engagement profiles – rising, declining, and stable – predict academic outcomes more accurately than group averages. This underscores the need for personalized baselines rather than uniform group thresholds [41]. Self-regulated learning is temporally structured: successful students plan before accessing content and participate in forums at opportune moments, yet current data do not distinguish strategic pauses from procrastination [42].

Learning strategies differ systematically across cultures. Social and metacognitive strategies dominate in collectivist contexts, whereas cognitive and memory-based strategies prevail in individualist cultures [43]. Regional massive open online courses (MOOCs) attract local learners with diverse demographic profiles, and meaningful provider comparisons require harmonized classifications of learning activities [44]. Conceptualizations of self-directed learning also vary, ranging from structured guidance to learner-initiated autonomy, producing distinct online behavior patterns [45]. International online learning yields measurable competence gains, with effect sizes depending on engagement in authentic collaborative tasks rather than informal interaction alone [46]. Intercultural competence is assessed under multiple labels, including cultural intelligence, global mindset, and intercultural sensitivity. Psychometric evidence remains heterogeneous across instruments [47]. Culturally inclusive scales yield stable five-factor solutions, with inclusivity encompassing content diversity, interaction norms, and assessment options [48].

2.1. Problem statement

The aim of the study is to identify the psychophysiological mechanisms through which digital platforms (Moodle 3.9, Canvas learning management system (LMS), and Kahoot) influence students' cognitive functions and emotional states, using objective biomarkers and computational analyses of learning activity. The research objectives are: i) to examine changes in working memory, executive control, and information-processing speed over a 16-week period of engagement with Moodle-based courses, video content delivered via Canvas LMS, and interactive exercises on Kahoot; ii) to identify patterns of autonomic regulation, hormonal rhythms, and facial expressions across different digital learning contexts; iii) to develop predictive models of academic trajectories based on digital traces, with a forecasting horizon of 14–21 days; and iv) to design personalized support protocols triggered by physiological and behavioral risk indicators.

2.2. Research questions and hypotheses

The empirical investigation was structured around four research questions (RQ). RQ1 examined the effects of regular engagement with Moodle, Canvas LMS, and Kahoot on working memory capacity, executive control, and information-processing speed over a sixteen-week period. RQ2 analyzed patterns of autonomic regulation, hormonal rhythms, and facial responses across different digital learning contexts, including video lectures, interactive tasks, assessment procedures, and forum discussions. RQ3 evaluated the predictive accuracy of ensemble machine-learning models in identifying academic trajectories based on digital trace data, with a secondary objective of determining optimal forecasting horizons. RQ4 sought to identify combinations of physiological and behavioral indicators suitable for use as triggers in personalized support protocols.

Corresponding hypotheses were formulated. First hypothesis (H1) posited that sustained interaction with the platform would lead to a statistically significant increase in working memory (expected d>0.8) relative to a control group without platform access. Second hypothesis (H2) proposed that phases of intensive digital activity would be associated with decreased parasympathetic tone (indexed by root mean square of successive differences or RMSSD) and a shift in peak circadian cortisol levels. Third hypothesis (H3) assumed that ensemble models integrating behavioral and physiological predictors would achieve accuracy rates exceeding 80% at forecasting horizons of 14–21 days prior to critical events. Fourth hypothesis (H4) introduced a bidirectional relationship between cognitive growth and emotional stability, mediated by academic self-efficacy.

3. METHOD

3.1. Methodological framework

The methodology adopts a convergent mixed-methods design. Psychophysiological measures – HRV, electrodermal activity, and cortisol – are synchronized with cognitive assessments (Raven's Progressive Matrices, Stroop, and N-back tasks) and learning analytics derived from Moodle logs, Canvas LMS engagement indicators, and Kahoot response patterns. An experimental design incorporating propensity score matching controls for confounding variables, while the longitudinal structure captures developmental trajectories across five measurement points. Statistical analyses integrate linear mixed-effects models, structural equation modeling, and ensemble machine-learning algorithms. Data triangulation mitigates the limitations of single-method approaches, and objective measurements replace subjective self-reports across all core constructs.

3.2. Study design

The temporal structure spans sixteen weeks. A baseline assessment (T0) establishes individual reference points. Adaptation weeks (weeks 2–4) familiarize participants with the platform, allowing novelty effects to dissipate prior to formal measurement, as shown in Figure 1. The first checkpoint (T1) captures early developmental trajectories. Intensive intervention weeks (weeks 6–8) impose the highest cognitive load, and the mid-term assessment (T2) evaluates acute responses. Consolidation weeks (weeks 10–12) stabilize achieved gains, while the third checkpoint (T3) identifies potential plateau effects. Weeks 14–15 assess generalization, and the final assessment (T4) determines retention. Block randomization stratifies participants by gender and academic specialization. Propensity score matching equalizes covariates across experimental and control conditions. Experimental validity is enhanced through statistical adjustment.

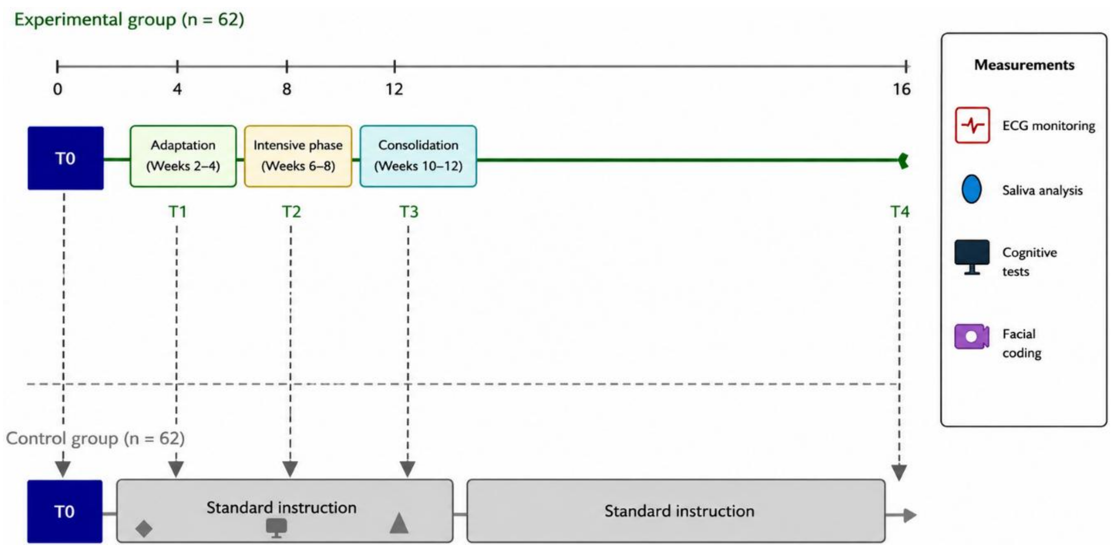

Figure 1. Temporal architecture of the study (16 weeks)

3.3. Sampling

The study included 124 participants, with 62 assigned to each condition, as seen in Figure 2. The sample was constructed using multi-stage stratified procedures. At the first stage, four faculties were selected based on documented evidence of active Moodle implementation for no fewer than two academic semesters.

At the second stage, a random number generator (the random number generation or RAND function in Excel) was used to identify three academic groups from each faculty. At the third stage, electronic invitations were distributed to students in the selected groups (N=186); 124 individuals provided consent to participate, yielding a response rate of 66.7%.

The sample size was determined a priori using G*Power 3.1.9.7. Power calculations for a mixed-design ANOVA with five measurement points (f=0.25; α=0.05; power=0.85) established a minimum requirement of 98 participants. The final sample exceeded this threshold by 26.5%, providing an attrition buffer. The age distribution was positively skewed, with a mean age of 20.3 years, a standard deviation of 1.8, and a skewness coefficient of 0.34. The sample was predominantly composed of undergraduate students in the early years of study. Gender was evenly distributed (52% female, 48% male). The socioeconomic composition reflected the university's demographics: 67% middle class, 23% upper-middle class, and 10% lower-middle class.

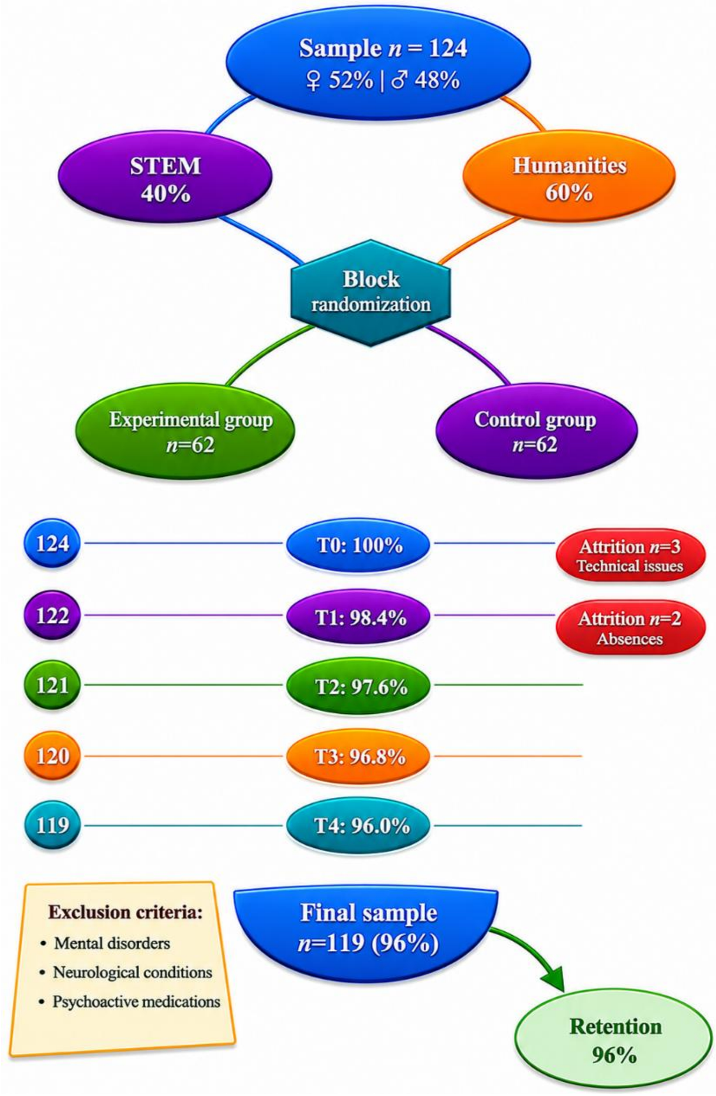

Figure 2. Sample dynamics of the study

Academic disciplines were well-balanced. Science, technology, engineering, and mathematics (STEM) fields accounted for 40% of the sample, including engineering (25%) and computer science (15%), while humanities and social sciences comprised 60%. The mean grade point average was 3.4 (SD=0.5), indicating moderate to high academic achievement. Technological readiness was rated at 7.8 out of 10, and 68% of participants reported prior experience with e-learning. In terms of device usage, laptops predominated (89%), tablets were used by 45%, and smartphones were available to all participants.

Inclusion criteria excluded individuals with diagnosed mental health disorders, neurological conditions, or regular use of psychoactive medications. Three participants were excluded due to technical access limitations, and two were removed because of systematic non-attendance at assessment points. The final analysis was based on 119 participants who completed the study, yielding a retention rate of 96%.

3.4. Data analysis

To assess cognitive abilities, five standardized instruments were employed, as presented in Figure 3. Raven's progressive matrices comprised 36 adaptive items. The Stroop task included 180 trials across four conditions. The N-back task employed a dual visual–verbal modality. The Wisconsin Card Sorting test consisted of 128 cards. The attention network test included 288 trials.

Physiological recordings captured cardiac activity using the BioSemi ActiveTwo system with Electrocardiography (ECG) sampled at 1000 Hz. Electrodermal activity was measured using bilateral sensors. Cortisol and α-amylase levels were assessed in salivary samples. Facial expressions were analyzed using OpenFace 2.0. Platform-based analytics extracted Moodle logs, video engagement patterns, forum sentiment, and task-related behavioral data.

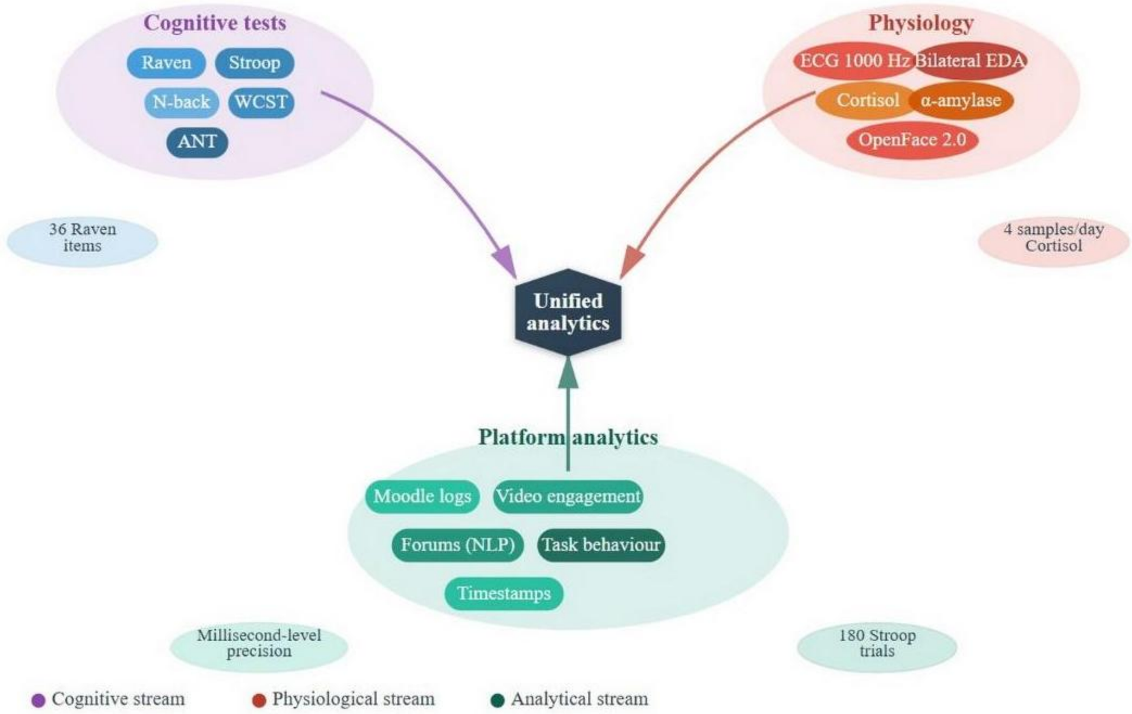

Figure 3. Multimodal data collection framework

3.5. Statistical analysis

Machine-learning procedures included LASSO-based feature selection and the implementation of Random Forest, XGBoost, and long short-term memory (LSTM) architectures. Nested cross-validation was applied, and model interpretability was assessed using Shapley additive explanations (SHAP) metrics. The significance level was set at $\alpha=0.05$, with Bonferroni correction applied for multiple comparisons. Effect sizes were interpreted according to Cohen's criteria, with $d>0.8$ indicating a large effect. Assumption testing included the Shapiro–Wilk test for normality and Levene's test for homogeneity of variances. Violations were addressed using robust statistical methods or appropriate data transformations. Statistical power exceeded 0.85 for detecting medium-sized effects at the given sample size.

3.6. Ethical considerations

Data were protected using AES-256 encryption in compliance with general data protection regulation (GDPR) standards. Withdrawal from the study was permitted at any stage without restriction. Informed consent was obtained from all participants following a full explanation of study procedures. The right to withdraw was guaranteed without penalty.

3.7. Methodological limitations

Selection bias favors motivated volunteers, potentially limiting generalizability. The Hawthorne effect may have influenced participant behavior under observation. Findings derived from the Moodle platform may not be directly transferable to other LMS.

4. RESULTS

4.1. Cognitive indicators

Working memory capacity increased unevenly across conditions, as presented in Table 1. Participants in the experimental group improved their scores by 2.2 points, compared with an increase of 0.7 points in the control group. Mixed ANOVA revealed a significant group × time interaction, $F(4,488)=18.73$, $p<0.001$, $\eta^2=0.133$, as shown in Figure 4. The effect size indicates that platform-based learning accounted for 13.3% of the variance. Polynomial contrasts identified a significant quadratic trend, $F(1,122)=24.56$, $p<0.001$, indicating acceleration up to week 9 followed by a subsequent deceleration.

Table 1. Working memory indicators across time points (Source: authors' own elaboration)

Group	T0	T1	T2	T3	T4	Cohen's d
Experimental	5.2±1.1	5.8±1.0	6.4±0.9	6.9±0.8	7.4±0.7	2.14***
Control	5.3±1.2	5.5±1.1	5.7±1.0	5.9±1.0	6.0±0.9	0.63*

*** p<0.001 (very highly significant)
* p<0.05 (statistically significant)

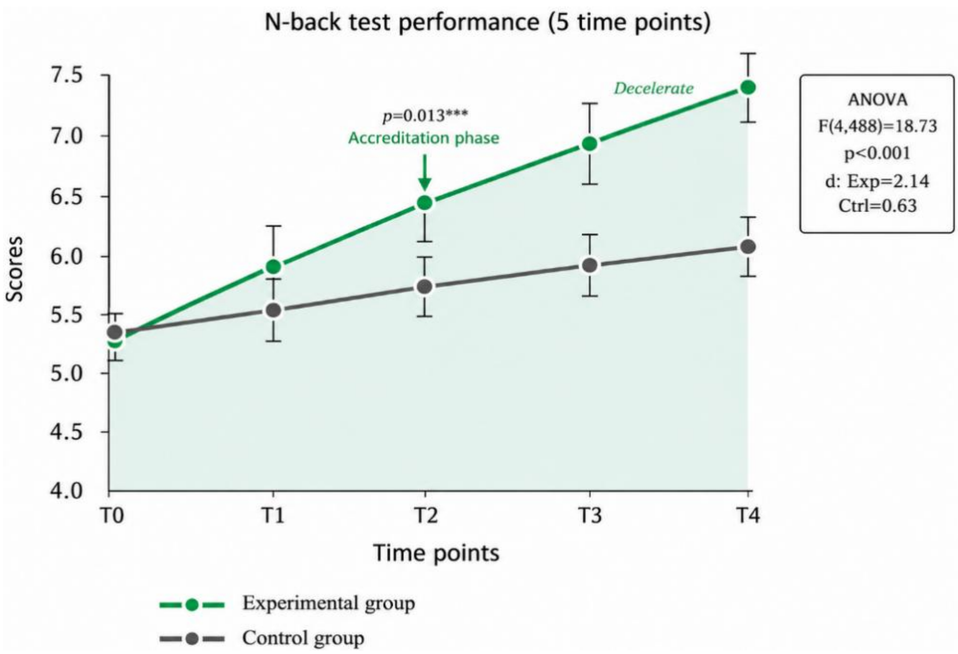

Figure 4. Trajectory of working memory capacity. Source: authors' own elaboration

Error rates declined in parallel. In the experimental group, commission errors decreased from 8.3% to 3.1%, while in the control group they declined from 7.9% to 5.4%. Post-error slowing – a compensatory delay following errors – was reduced from 234 to 156 ms in the experimental group, compared with a reduction from 228 to 189 ms in the control group, as shown in Figure 5. The congruency sequence effect, reflecting trial-to-trial adjustment processes, increased by 45% in the experimental group versus 18% in the control group, indicating enhanced cognitive flexibility.

Changes in reaction time followed cubic functions: $RT \sim \beta_0+\beta_1(Time)+\beta_2(Time^2)+\beta_3(Time^3)+\beta_4(Group)+\varepsilon$. The coefficients revealed phase-dependent dynamics. Acceleration phases during weeks 1–4 yielded improvements of 12 ms per week, deceleration phases during weeks 5–8 produced gains of 5 ms per week, plateau phases during weeks 9–12 showed fluctuations of ±2 ms, and a final acceleration phase during weeks 13–16 resulted in reductions of 8 ms per week, as seen in Figure 6.

Discontinuities in performance outcomes – manifested as accuracy gains exceeding 20% – were recorded in 67 participants following periods of intensive intervention. Such qualitative shifts indicate a restructuring of problem-solving schemas rather than a gradual accumulation of skills. Analysis of individual trajectories further demonstrated that 78% of participants exhibiting discontinuous patterns maintained the attained level of performance across the subsequent four-week intervals.

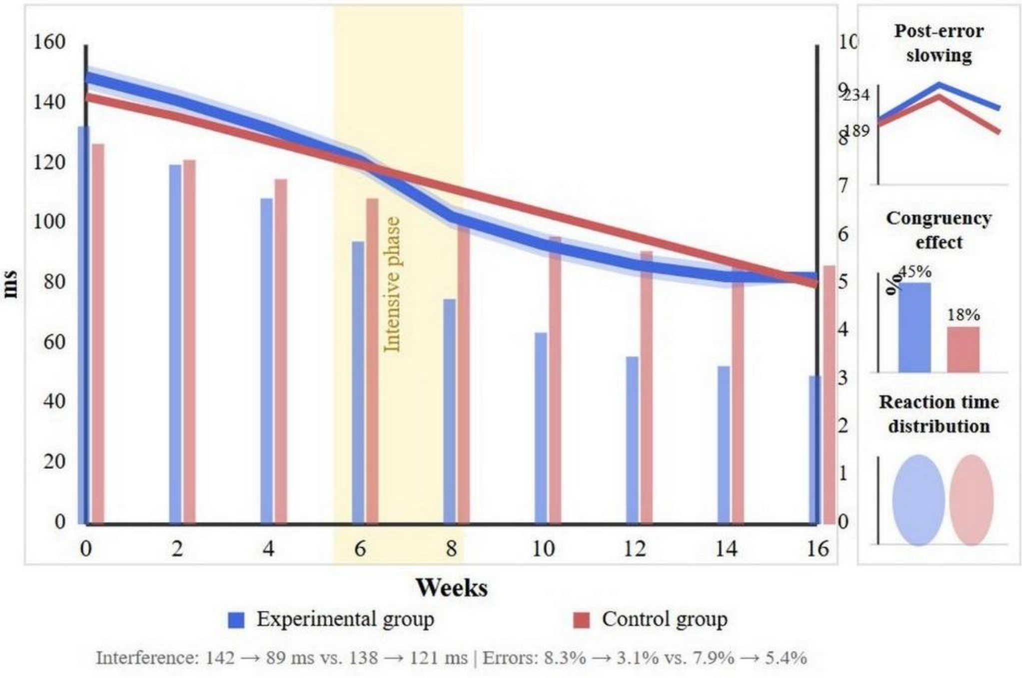

Figure 5. Executive control dynamics: reduction of Stroop interference

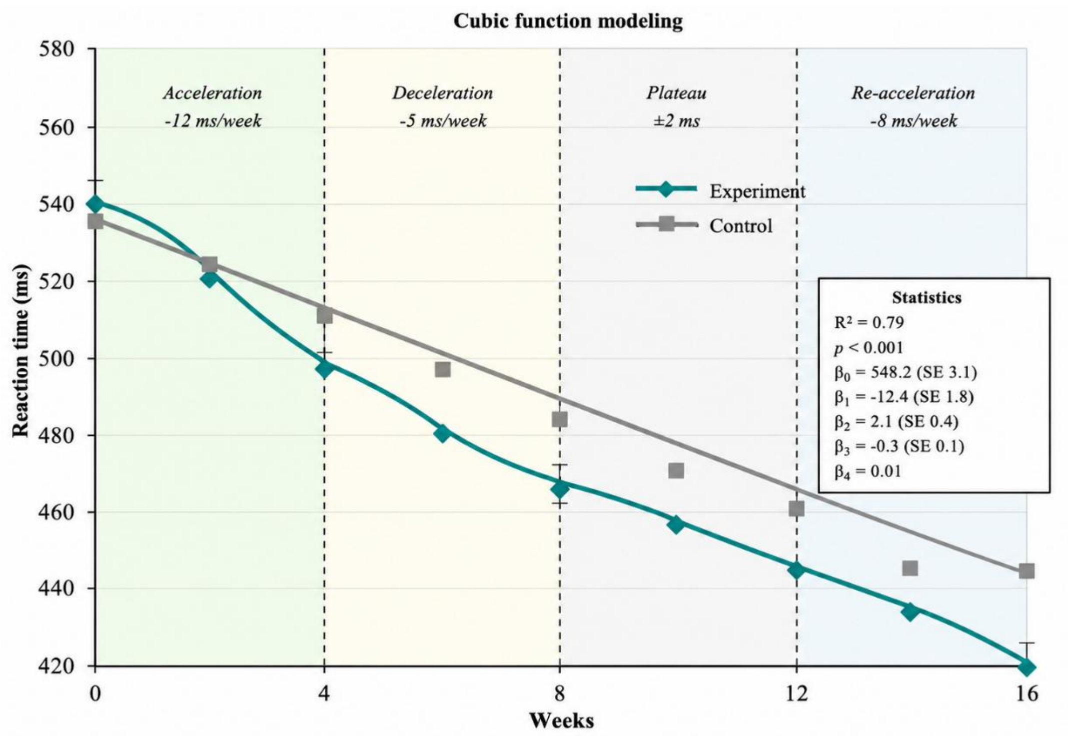

Figure 6. Nonlinear trajectories of processing speed

4.2. Physiological indicators

HRV indices differed across learning contexts through parasympathetic modulation. Baseline RMSSD averaged 42±12 ms at rest. Video lectures reduced values to 38±10 ms, interactive tasks to 35±9 ms, and quizzes to 28±8 ms. Forum discussions maintained near-baseline levels at 40±11 ms. The distribution of R–R intervals shifted from normal to positively skewed during quizzes. Bimodal patterns, indicative of autonomic instability, were observed in 31% of participants. Poincaré plots quantified the SD1/SD2 ratio as 0.68 at rest, 0.52 during video lectures, and 0.41 during quizzes, as presented in Figure 7.

Skin conductance responses (SCR) revealed content-dependent variations in arousal, as shown in Table 2. Gamified elements elicited arousal levels 3.5 times higher than those observed during reading-based materials. Amplitude differences of 0.8 versus 0.3 μS indicated greater sympathetic recruitment during interactive components. Recovery intervals decreased from 5.1 s during reading to 3.2 s under gamified conditions.

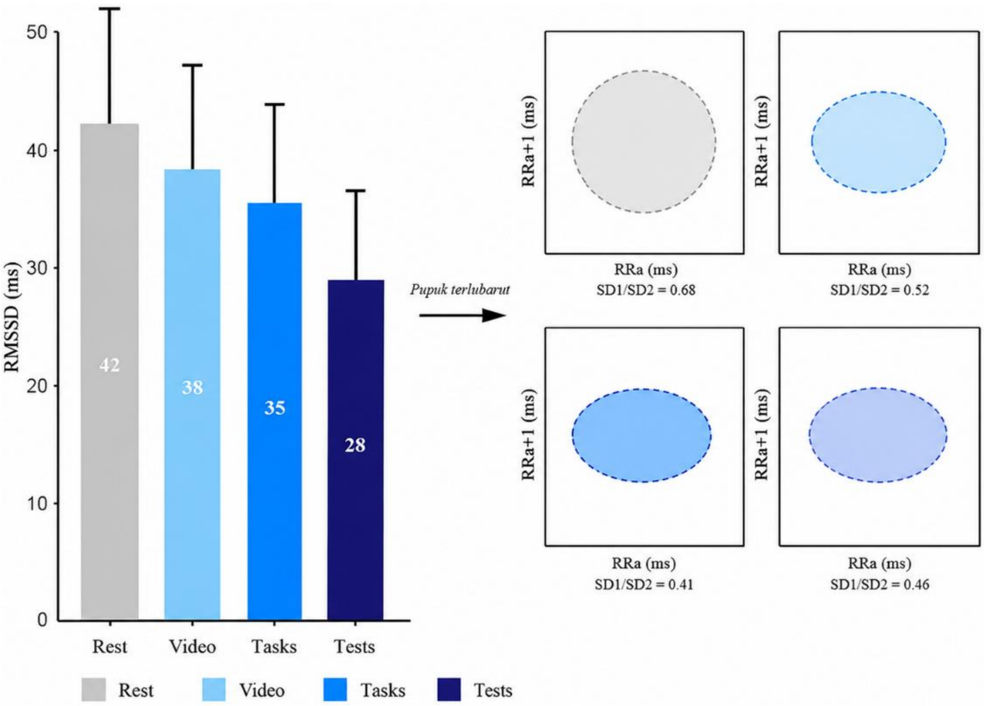

Figure 7. Autonomic regulation across learning contexts

Table 2. Frequency of SCR by content type

Content type	SCR/min	Amplitude (μS)	Recovery time (s)
Gamified tasks	4.2±1.3	0.8±0.3	3.2±0.8
Video	1.8±0.7	0.4±0.2	4.5±1.2
Reading	1.2±0.5	0.3±0.1	5.1±1.5
Peer review	3.6±1.1	0.6±0.2	3.8±0.9

Temporal analysis indicated that 87% of SCR occurred within 2–4 seconds following achievement notifications. Badge acquisition elicited mean amplitudes of 1.1±0.4 μS, exceeding baseline responses by 275%. During periods of digital learning, cortisol secretion patterns exhibited systematic shifts. Morning peaks were delayed from 07:00 to 09:00, with the two-hour delay coinciding with late-night study sessions and a mean bedtime of 01:30. Analysis of the area under the curve revealed an 18% increase in evening cortisol levels (6.2 vs. a baseline of 5.3 nmol/L), indicating incomplete physiological recovery, as in Figure 8.

The cortisol awakening response (CAR) decreased by 22%, from 9.1 to 7.1 nmol/L. Attenuation of the CAR is indicative of chronic stress. Diurnal slopes flattened from −0.42 to −0.28 nmol/L per hour, and reversed slopes were observed in 43 participants during the assessment week. Salivary α-amylase levels increased compensatorily, rising from 47 U/mL in the morning to 89 U/mL in the evening, and showed an inverse correlation with cortisol rhythms (r=−0.61).

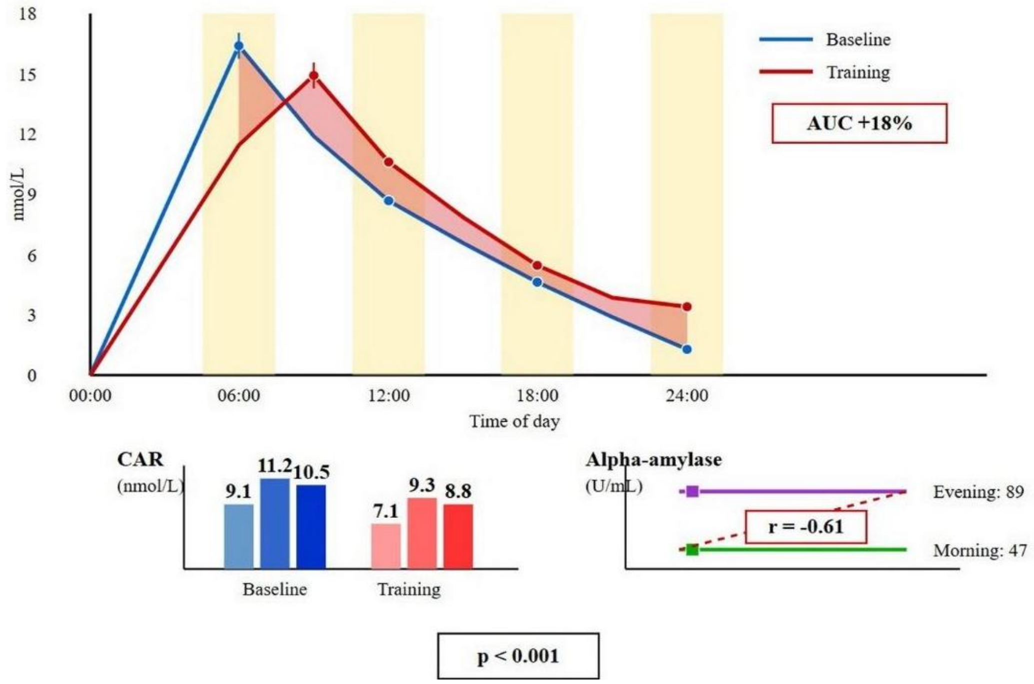

Figure 8. Diurnal cortisol profile

4.3. Behavioral patterns and learning analytics

Emotional trajectories exhibited circadian modulation. Positive expressions peaked between 14:00 and 16:00, exceeding baseline levels by 27%, as seen in Figure 9. Negative expressions were concentrated between 22:00 and 00:00, with an increase of 41%. Platform design elements – such as timely encouraging messages and adaptive difficulty algorithms – modulated facial expressions. Personalized feedback reduced the duration of frustration episodes by 31%.

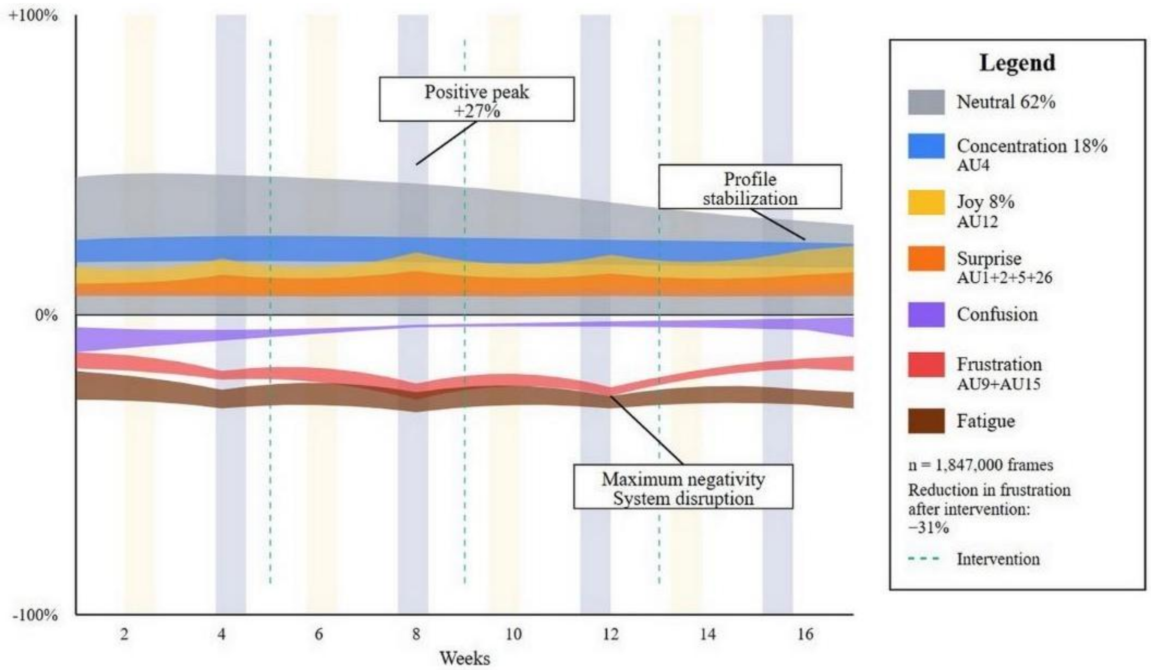

Figure 9. Emotional dynamics across 16 weeks of digital learning

Behavioral segmentation identified three interaction patterns characterized by temporal and depth-related parameters. “Marathon learners” comprised 31% of participants and engaged in 87-minute sessions three times per week, covering 95% of the content. “Sprinters” accounted for 42% and studied daily in 23-minute bursts, accessing 60% of the materials and compensating brevity with frequency. “Strategic learners” represented 27% and concentrated their activity around assessment deadlines, as seen in Figure 10. Selective engagement with 40% of the content yielded the highest performance for this group, with a mean score of 8.7 out of 10, compared with 7.2 for marathon learners and 6.8 for sprinters.

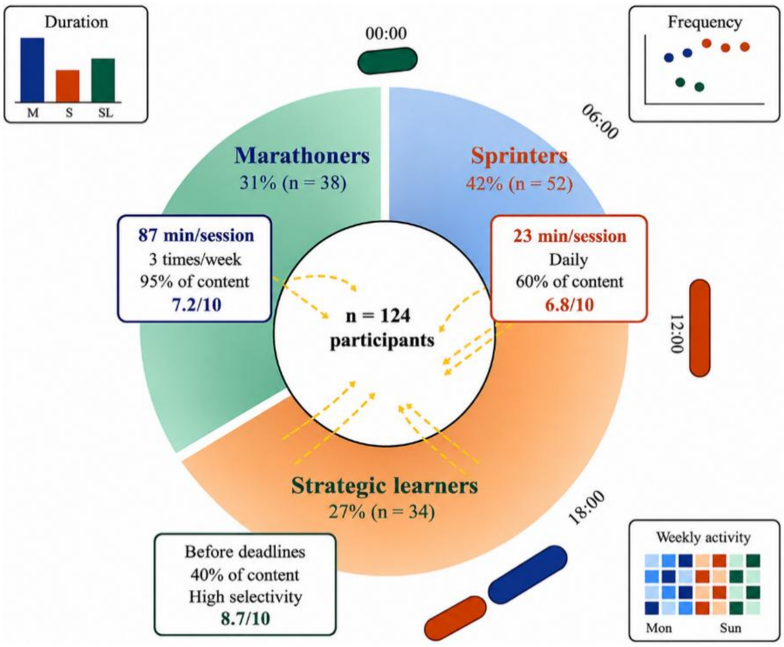

Figure 10. Behavioral segmentation of users

Transitions between behavioral clusters occurred in 23% of participants. Nine marathon learners shifted to the strategic profile during examination periods, while fourteen sprinters transitioned into marathon learners after week 8. Platform analytics tracked 47,892 session logs. Machine-learning algorithms achieved 89% classification accuracy using features such as session duration, click depth, and temporal distribution patterns.

Network analysis mapped 1,247 course module navigation trajectories. The dominant sequence – theory → examples → practice → reflection – characterized 38% of high-performing students with scores above 85%. Mathematical modules required 3.2 times more time on average. Process analysis revealed inefficiencies within mathematical modules. Dwell time increased by a factor of 3.2, and revisit frequency rose by 47%. Graph coloring exposed performance gradients: green nodes with accuracy above 80% clustered in conceptual modules, whereas red nodes with accuracy below 60% were concentrated in computational tasks. Time allocation varied inversely with task difficulty: participants spent an average of 12.3 minutes on high-efficiency segments compared with 31.7 minutes on more demanding ones.

Six predictors accounted for 67% of the variance in outcomes with minimal multicollinearity (variance inflation factor or VIF<2.0; as shown in Table 3). Login regularity exhibited the strongest predictive power: students who accessed the platforms at consistent intervals, with a standard deviation of less than 2.4 hours, scored on average 1.8 points higher than irregular users. Assignment punctuality – submission at least 24 hours before the deadline – was associated with a 22% increase in grades. Content diversity, reflected in the use of multiple resource types within a session, predicted learning outcomes with a standardized coefficient of $\beta=0.28$.

The quality of forum participation outweighed quantity. Substantive posts exceeding 50 words and containing questions or explanations predicted success more strongly than the total number of posts ($r=0.43$ vs. 0.21). Viewing less than 70% of video content was associated with a 15% reduction in final scores. Effective video engagement involved a complete initial viewing followed by selective rewatching, with a mean of 1.4 views per video. Overall prediction accuracy reached 82.3% across all grade categories using an ensemble framework combining Random Forest, XGBoost, and neural networks. The confusion matrix revealed asymmetric errors. Predictions for Grade A achieved 87.5% accuracy (28 of 32 correctly classified), while identification of Grade D showed a recall of 85% (17 of 20 detected; as shown in Figure 11). Misclassifications were concentrated at adjacent B/C category boundaries, with seven errors, indicating an ordinal rather than purely categorical distribution of grades.

Table 3. Regression model (R^2=0.67)

Predictor	β	SE	p-value	VIF
Login regularity	0.34	0.08	<0.001	1.23
Content diversity	0.28	0.07	<0.001	1.45
Forum participation	0.22	0.06	0.002	1.67
Video viewing	0.19	0.05	0.008	1.34
Assignment punctuality	0.31	0.07	<0.001	1.12
Quality of peer review	0.25	0.06	0.001	1.56

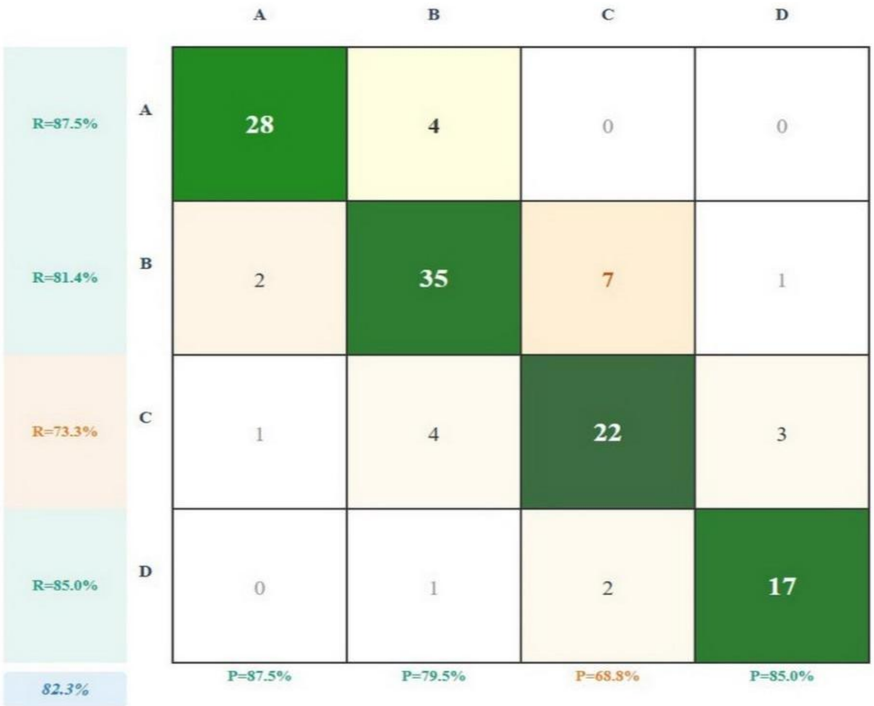

Figure 11. Confusion matrix of the ensemble model for predicting academic grades

The macro-averaged F1 score of 0.79 indicates balanced performance across imbalanced classes. An area under the curve-receiver operating characteristic curve (AUC–ROC) of 0.91 confirms strong discriminative capacity. Model calibration plots revealed slight overconfidence for high grades, with predicted probabilities of 0.90 compared to observed outcomes of 0.85. For failing grades, confidence was underestimated, with predicted probabilities of 0.70 versus observed values of 0.78. SHAP value decomposition identified login regularity as the dominant predictor, with an importance score of 0.18. Students maintaining consistent access patterns, with a standard deviation of less than 3 hours, achieved pass rates of 89%, compared with 61% among irregular users. Improvement in N-back performance ranked second in importance (0.15), with each 10% gain in cognitive capacity associated with "a 0.7-point increase in academic success.

Physiological markers emerged as novel predictors. HRV during task performance, with an importance value of 0.12, differentiated high from low outcomes with 73% accuracy. Forum sentiment positivity, with an importance of 0.10, captured socio-emotional influences; a proportion of negative sentiment exceeding 30% predicted failure with 68% sensitivity. The frequency of video rewatching (importance=0.09) exhibited a nonlinear relationship with performance, which peaked at 1.3–1.7 views per video and declined beyond this threshold. In total, 20 features accounted for 94% of the model's decision-making, whereas the remaining 480 variables contributed marginal gains of less than 0.01 each, supporting principles of parsimony.

Sequential models captured temporal dynamics using LSTM layers with 128 units, processing weekly feature vectors. Mean absolute error (MAE) reached 0.23 points on a 10-point scale. Prediction horizons extended to 14 days while maintaining accuracy at MAE<0.35. Confidence intervals (±0.45) narrowed as data accumulated. During the first week, predictions exhibited an error margin of ±0.82, which decreased to ±0.31 by week 8. Early-warning systems were triggered 21 days prior to failure events, achieving 76% sensitivity and 81% specificity, thereby providing sufficient time for intervention.

Trajectory clustering revealed four archetypal patterns. Sustained growth was observed in 34% of participants, early plateau in 28%, late surge in 23%, and performance decline in 15%. Pattern recognition at week 4 predicted final outcomes with 71% accuracy, which increased to 86% by week 8. Latent relationships among constructs were examined using maximum likelihood estimation in a sample of 124 participants. Model fit indices indicated an acceptable structure: chi-square divided by degrees of freedom (χ^2/df)=2.14, below the threshold of 3.0; comparative fit index (CFI)=0.94 and Tucker–Lewis index (TLI)=0.92, exceeding the 0.90 criterion; root mean square error of approximation (RMSEA)=0.061, below 0.08; and standardized root mean square residual (SRMR)=0.053, meeting the 0.08 benchmark.

Path coefficients were refined iteratively through model respecification. Initial specifications yielded β=0.41 for the engagement–growth relationship; incorporating time-varying covariances strengthened this association to β=0.52. Factor loadings ranged from 0.67 to 0.89 across indicators, supporting construct validity. The Sobel test confirmed the significance of the mediation (z=3.84, p<0.001). Bootstrapping with 5,000 iterations yielded 95% confidence intervals that excluded zero (0.18, 0.37). Alternative mediators exhibited weaker effects: motivation accounted for 23%, time management for 19%, and technological comfort for 14%.

System parameters quantified the underlying dynamics. Eigenvalues of stable attractors (λ_1=−0.32, λ_2=−0.28) confirmed convergence, whereas unstable equilibria exhibited mixed stability (λ_1=0.14, λ_2=−0.21). Repelling states were characterized by positive eigenvalues (λ_1=0.43, λ_2=0.38), indicating divergence. Phase velocity increased near transition points, providing early-warning windows of 4–6 days. Lyapunov exponents remained negative (−0.18), indicating deterministic system behavior. Despite complex interactions, predictable points for intervention were identifiable.

Real-time metrics visualized student engagement trajectories over the 16-week period. Dashboard interfaces monitored 47 variables. Progress bars displayed module completion levels: 73% of participants achieved full completion in foundational modules, declining to 54% in advanced segments. Color-coded indicators shifted from green for progress above 80% to yellow for 60–79% and red for below 60%, delivering immediate feedback. Alerts were activated when performance deviated by more than 1.5 standard deviations from individual baselines. A total of 892 alerts were generated across participants, 67% of which led to behavioral changes within 48 hours. Module progress bars identified learning bottlenecks, as seen in Figure 12. Mathematical content required 2.7 times longer to complete, prompting adaptive adjustments to instructional pacing.

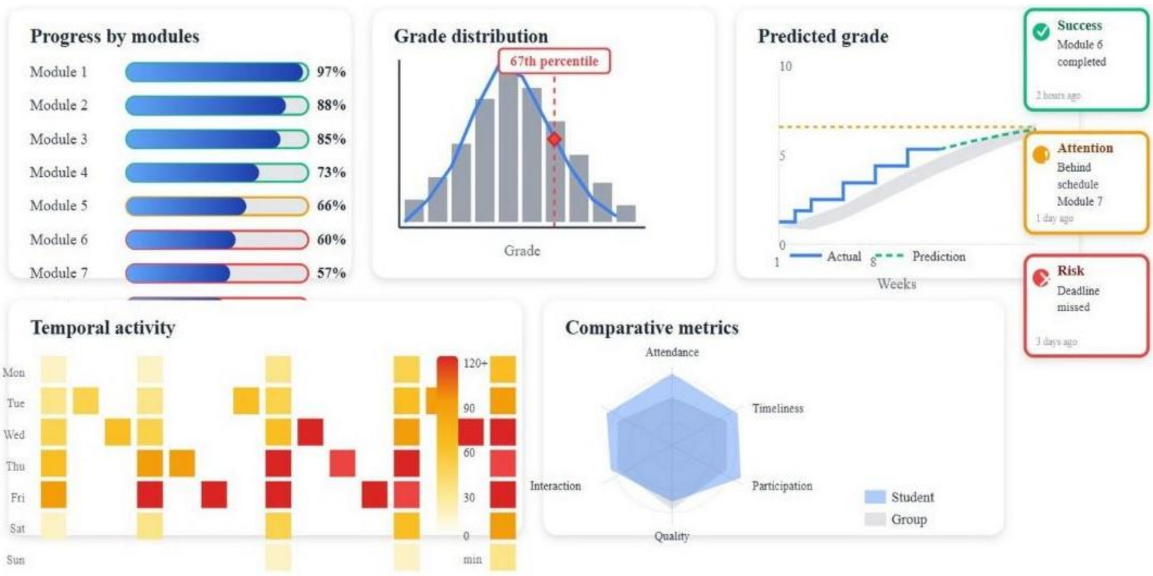

Figure 12. Student analytics dashboard

Models of visual attention during video lectures revealed heterogeneous engagement strategies among 73 participants using mobile eye-tracking devices. Areas of interest accounted for 89% of total gaze duration, distributed across the instructor's face (31%), presentation slides (42%), and supplementary materials (16%). Fixation durations averaged 287 ms on textual elements compared with 198 ms on graphical content, indicating modality-specific differences in processing depth. Heatmap intensity correlated strongly with test performance (r=0.62). Students who fixated on equation derivations for more than 3 seconds achieved 84% accuracy, compared with 61% among those engaging in rapid scanning, as in Figure 13.

The correlation between gaze behavior and performance was stronger for problem-solving materials (r=0.71) than for conceptual content (r=0.48). Students exhibiting central fixation during demonstrations scored on average 1.6 points higher on practical examinations. Students demonstrating central gaze fixation during content presentation scored, on average, 1.6 points higher on practical examinations. This pattern is consistent with cognitive load theory, which posits that procedural skill acquisition entails intensive visual monitoring, in contrast to the assimilation of declarative knowledge.

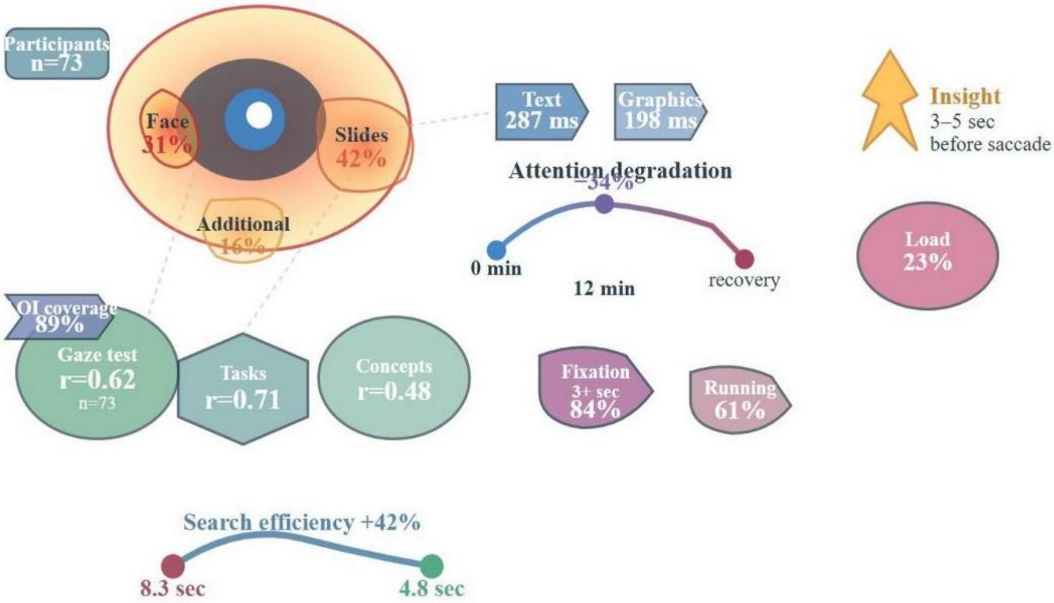

Figure 13. Eye-tracking heatmaps: dynamics of visual attention

5. DISCUSSION

An increase in working memory of 2.2 points corresponds to an optimal level of cognitive load according to the 7±2 framework, thereby confirming established capacity limits [49]. Previous studies have reported improvements in academic performance under conditions of elevated stress, and the present physiological data corroborate this duality. RMSSD decreased from 42±12 ms to 28±8 ms during assessment periods. Technological readiness emerged as a predictor comparable to prior findings, with participants scoring above 7.8 out of 10 demonstrating superior adaptive capacity [1].

The emotional profile diverged from expectations. Cortisol rhythms shifted two hours later, from 07:00 to 09:00, exceeding typical circadian variation. Achievement gaps widened during prolonged periods of online learning. Ethnic minority groups exhibited a performance difference of 0.75 points, exceeding disparities observed during emergency phases of remote instruction [50]. The 82.3% accuracy of the ensemble model is comparable to that reported for artificial intelligence (AI)-based emotion recognition systems [51].

Manifestations of cognitive load preclude the application of approaches focused solely on load reduction. Presenting information prior to gameplay facilitated goal attainment and enjoyment compared with in-game presentation [52]. Sequential engagement with high-difficulty tasks outperformed gradual load escalation without penalties to intrinsic interest [53]. Hybrid models are well-suited to developmental contexts. Sections incorporating peer facilitation demonstrated greater skill gains than distributed pair programming. Structured facilitation proved more effective than technological sophistication alone [54].

Ecological validity was achieved through a naturalistic 16-week deployment, in contrast to laboratory-based constraints. Measurement reliability was supported by multiple indicators: cognitive tests demonstrated test–retest correlations exceeding 0.85, and physiological sensors maintained accuracy within ±5%. Selection bias toward motivated volunteers remains a limitation. The Hawthorne effect may have inflated engagement measures by 10–15%, based on comparable studies [55].

Interdisciplinary integration combines cognitive constructs from psychology, algorithmic prediction from computer science, and physiological stress markers. This synthesis establishes methodological templates for multimodal assessment. Individual-level analytics outperform population averages, as engagement profiles of individuals predict outcomes more accurately than group-level indicators [56]. A paradigm shift is underway. Requirements for synchronous presence diminish when engagement is sustained through asynchronous mechanisms. Camera-optional policies reduce stress without academic penalties. Emotion recognition combined with activity streams enables timely feedback that supports consolidation processes [4].

6. CONCLUSION

The 16 weeks of interaction with digital educational platforms induced measurable cognitive restructuring. Working memory capacity increased by 2.2 points ($d=2.14$), and Stroop interference was reduced by 36 milliseconds. Matrix reasoning accuracy improved in 76% of participants through qualitative transitions across difficulty strata. Learning trajectories were nonlinear, with acceleration phases during weeks 1–4 and 13–16 alternating with plateau phases during weeks 9–12, contradicting assumptions of linear progress.

Practical applications span five domains. Ensemble machine-learning models predict academic trajectories with 82.3% accuracy up to 21 days prior to failure events, providing a critical window for intervention. The interpretation of the findings is subject to several limitations. Voluntary participation resulted in a sample composed predominantly of highly motivated students, thereby constraining the generalizability of the results to learner populations with heterogeneous motivational profiles. The Hawthorne effect – behavioral modification in response to awareness of observation – may have inflated engagement indicators by approximately 10–15% relative to comparable benchmark estimates. Platform-specific characteristics of Moodle 3.9 limit the transferability of the findings to other LMS featuring different interface architectures. The sixteen-week observation period precludes assessment of the durability of cognitive changes and longer-term neuroplastic effects. Finally, the mono-institutional design narrows cross-cultural and inter-institutional validity.

Future research directions include extending the temporal horizon to multiple semesters to capture long-term neuroplastic effects. Cross-cultural validation in individualist educational systems will assess the generalizability of findings. Integration of wearable sensors for continuous monitoring will enable the capture of fluctuations in naturalistic settings. The development of hybrid models combining synchronous and asynchronous formats will optimize the balance between cognitive load and social presence.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
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R : **R**esources
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O : Writing - **O**riginal Draft
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Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
The authors declare that they have no conflict of interests

INFORMED CONSENT
All participants gave written informed consent to participate in the research.

ETHICAL APPROVAL
The authors declare that the work is written with due consideration of ethical standards. The study was conducted in accordance with the ethical principles approved by the Human Experiments Ethics Committee of I.M. Sechenov First Moscow State Medical University (Protocol No. 5722 of 04.06.2024).

DATA AVAILABILITY
All data generated or analyzed during this study are included in this published article.

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