

Cognitive Load Management in Educational Contexts: An Analysis of Physiological Measurements for Personalised Learning

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Abstract. Educational institutions and corporate training departments face constant pressure to optimise learning outcomes while reducing costs. This study examines the economic and practical implications of using physiological metrics, such as blink rate, as indicators of cognitive load in educational contexts. The Cognitive Load Theory (CLT), as studied to date, provides theoretical and empirical support for developing instructional materials tailored to an individual's learning needs. This approach could help instructors adapt their teaching techniques to how students or training participants build and use understanding, providing a personalised learning experience tailored to an individual's learning style. This study examines whether relationships exist between objective physiological metrics (e.g., blink rate) and subjective metrics, and between these metrics and cognitive load, in a sample of undergraduate students from Politehnica University of Timisoara who were solving specific tasks. For objective physiological metrics, an eye-tracking experiment was employed; for subjective measures, a 7-point scale was used, in which study participants rated their perceived cognitive load for two evaluation tasks. The sample is not necessarily a proxy for corporate learners but represents the future workforce undergoing formative educational experiences. Research suggests that a physiological metric, such as blink rate alone, is not a reliable sign of cognitive load. Self-reported effort, however, distinguishes high performers from underperforming students. Our study investigates the nature of the relationship between this objective measure and subjective metrics to clarify whether and under what conditions these measurements can be considered valid indicators of perceived effort.

Keywords: physiological monitoring, stress management, adaptive learning, cognitive load measurement, eye-tracking metrics, learning styles, blink rate analysis.

Introduction

Global e-learning marketing has grown rapidly in recent years, with an estimated value of \$ 325 billion in 2025 (The Business Research Company, 2025). This growth is driven by adaptive learning technologies that promise to personalise training and instruction based on the trainee's cognitive state. These systems assume that cognitive load can be reliably measured and used to trigger instructional adaptations.

From an economic perspective, physiological monitoring of certain metrics during the learning process has the potential to reduce three types of educational costs: (a) the costs of inefficiency generated by a mismatch between the difficulty of the content and the participants' level of knowledge, (b) the costs of burnout when students disengage due to cognitive overload, and (c) the costs of remediation when learning objectives are not achieved upon first exposure to the learning content. If physiological metrics could support the measurement of cognitive overload, adaptive systems can be used proactively, potentially generating cost savings. The theoretical foundation assumes that

cognitive load requiring sustained attention is associated with reduced blink rate (Nakano et al., 2013). Despite the debate over validation, blink rate has been widely used in cognitive load studies and applications. Blink rate has been used in various commercial tools, including educational, driver-monitoring, and work-assessment tools, despite ongoing scientific debate.

Cognitive load theory (CLT) was developed in the 1980s by Sweller ((Sweller, 1988) and has become the foundation of educational psychology and instructional design. The CLT was applied to predict variations in learning outcomes using specific instructional designs (Sweller, 2011; Sweller, 2017). Understanding human cognitive architecture, particularly the constraints of working memory on the processing of new information, is foundational to CLT (Swulmowski and Xu, 2022). At this point, cognitive load theory distinguishes among three types of cognitive load: intrinsic, extraneous, and germane. The inherent load relates to the intrinsic complexity of the course content that the instructional design cannot change. The extraneous load is produced by ineffective instructional design. It can be reduced through improved teaching methods. The germane load refers to the mental effort devoted to schema construction and automation, which is beneficial because it directly contributes to learning and understanding (Evans et al., 2024).

This study aims to identify the following gaps: a) the need to explore systematic individual differences that can moderate the correlations between physiological metrics and cognitive load; b) exploring the idea that the monitoring of cognitive load requires the same individualised and context-sensitive approach supported in stress management frameworks.

Based on these knowledge gaps, the study specifically investigates how blink rate measurements and self-assessments differ across two task conditions. Using screen-based eye-tracking data from iMotions, we could objectively measure physiological variables, such as blink rate, as learners engaged in tasks with varying complexity and formats. This approach allowed us to investigate the relationship between certain eye-tracking indicators and cognitive load in real time.

Review of the literature and development of research questions

In recent years, several discussions have emerged regarding the concept of learning styles and their connection to inclusive education. According to Gudnason (2017), adapting training to individual learning styles may not be as successful as previously believed. Although learning styles were frequently advocated, an analysis of teacher education literature revealed little empirical evidence supporting their effectiveness in learning environments (Cuevas, 2015). Olanrewaju Adebisi (2024) acknowledges that learners acquire knowledge differently and examines a range of frameworks, as evidenced by the literature and global surveys. The research explains the concept of differentiated training and guides on implementing it in inclusive learning environments to support equality among all learners. In education, the flexibility of instructional approaches to diverse cognitive needs can improve performance and learning outcomes by reducing cognitive load on learners (iMotions, 2023).

Most research on cognitive load assesses the efficacy of teaching techniques that consider working memory limitations rather than explicitly measuring cognitive load, as noted by the Centre for Education Statistics and Evaluation (2017). It is critical to use objective, non-intrusive, real-time techniques to monitor each form of cognitive load. The ability to continually and non-intrusively observe learners in real time makes eye-tracking techniques promising. Additionally, eye-tracking has been shown to distinguish between tasks with low and high cognitive loads (Zu et al., 2017). Contemporary eye-tracking research has expanded from traditional fixation metrics to include physiological indicators such as blink rate, pupil dilation, and saccades (Sáiz-Manzanares et al., 2024). The physiological systems that respond to physiological stress (Rachmad,

2022) are the same as those activated during cognitive load. The relationship between cognitive load and stress has been well documented in the literature (Rachmad, 2022; Sweller, 2011). In Stress Management Theory, Rachmad (2022) outlined that a specific manifestation of the more general stress response is the cognitive load during learning. Learners experience a form of cognitive stress characterised by both physiological responses and subjective perceptions of effort when faced with information-processing demands that are near or above their working memory capacity (Sweller et al., 2011). The framework developed by Rachmad (2022) offers a useful perspective on the complexity of measuring cognitive load. Theoretically, three fundamental ideas that are directly relevant to educational settings are identified: personalised evaluation and intervention are necessary due to individual variability in stress responses; multimodal measurement, which combines physiological and subjective indicators, offers a more detailed understanding than single-method approaches; and contextual factors, such as social support and environmental conditions, moderate the relationship between stress and response.

Physiological measures such as blink rate, pupil dilation, and heart rate variability respond to both emotional stress and cognitive demands. When information-processing demands exceed working memory capacity, the result is a form of cognitive stress that manifests itself both physiologically and subjectively. This idea provides a theoretical basis for applying stress management principles to cognitive load monitoring. Recent analyses of physiological cognitive load measures (Chakladar & Roy, 2023) confirm moderate correlations between blink rate and task difficulty in laboratory settings but also highlight substantial individual differences and replication challenges. However, validation studies also reveal significant limitations, including individual baseline differences, environmental sensitivity to factors such as display brightness, and context-dependent reliability across various cognitive domains. Our study, in the context of multimedia learning, addresses this gap by validating limitations in blink-rate indicators.

Sweller et al. (2019) state that cognitive load theory provides evidence-based principles for creating concise instructional messages and units, including lessons, textual materials (text and images), and educational multimedia such as animations, videos, simulations, and games. It aligns with many aspects of mental workload models that emphasise workplace performance over learning and instructional design (Wickens, 2008), as well as with the cognitive theory of multimedia learning, which concentrates solely on the design of multimedia resources (Mayer, 2014). Students who received customised training for their learning styles showed notable improvements in academic performance and retention (Buciuman and Potra, 2024). By adapting teaching methods to students' learning styles and creating a tailored learning environment, trainees can perform better and achieve better outcomes (El Guabassi et al., 2019). Some effective strategies for creating an inclusive learning environment that caters to diverse learning styles can be discussed.

Van Merriënboer and Kirschner (2018) describe a ten-step practical version of the 4C/ID model for teachers and educational designers to help them develop academic and training programmes that facilitate the acquisition of complex cognitive skills. The fundamental premise of the Ten Steps approach of the 4C/ID model is that learning tasks, procedural information, supportive information, and part-task practice are the four fundamental elements that can always be used to characterise blueprints for complex learning. There is substantial variability across the set of learning activities, which are organised into training sessions that range from easy to challenging. Additionally, learner support decreases with each task class (van Merriënboer and Kirschner, 2018). Researchers and professionals in visual computing are currently striving to minimise unnecessary cognitive load, allowing most working memory resources to be allocated to effective learning through optimal instructional material design.

To investigate the relationship between objective and subjective measures of cognitive load, we first examined the methods used to obtain objective measures. Sweller et al. (2019) emphasised that no single measure adequately captures the multidimensional nature of CLT; therefore, we examined this claim.

This study proposes a framework that integrates blink rate measurements with self-assessment in two task conditions. Our research questions are as follows:

RQ1: What is the relationship between blink rate as a physiological indicator and subjective evaluations of cognitive effort in educational processing contexts?

RQ2: Which individual and contextual factors moderate the relationship between objective measurements and performance in complex cognitive tasks?

RQ3: What are the implications of the identified correlations for the development of adaptive learning systems based on physiological monitoring?

By addressing these research questions, the study aims to provide answers both to the theoretical measurement of cognitive load and to guide individualised educational paths.

Methodology

Our research framework comprises a series of steps, beginning with the formulation of research questions and an analysis of the existing literature on cognitive load theory and eye-tracking as an investigative tool in educational research. The research design includes the development of study materials and a pre-test of the data collection method to guarantee the reliability and validity of the findings, as seen in Figure 1.

The study sample comprised 30 undergraduate students from Politehnica University Timisoara, with an age range of 20-25. All were Romanian native speakers with normal or corrected-to-normal vision; there were 18 females and 12 males. For the eye-tracking experiment, we used the iMotions screen-based tracker under similar environmental conditions (noise, lighting, and temperature) and hardware settings. The iMotions eye-tracker provides comprehensive tools for measuring visual attention by tracking eye movements, gaze points, and pupil size across images, videos, and other screen-based stimuli.

The learning style profiles for this sample of students were previously established through an assessment using the Felder-Silverman Learning Style Model, conducted as part of a separate validation study (Buciuman and Potra, 2024). The prior study allowed us to examine the relationship between established learning preferences and eye-tracking behaviour patterns. Eighty-five per cent of the students were active learners. Additionally, while 21% of students preferred abstract knowledge, 79% were sensory learners who preferred physical, practical, or methodical information, as analysed in a previous study of the same sample. Regarding information intake, most attending students (77%) were visual learners who strongly preferred visual content, such as pictures or videos. Analytical thinking and a holistic approach to learning are equally prevalent among the sample of students, as evidenced by comparable proportions of sequential and global learners in their understanding of information.

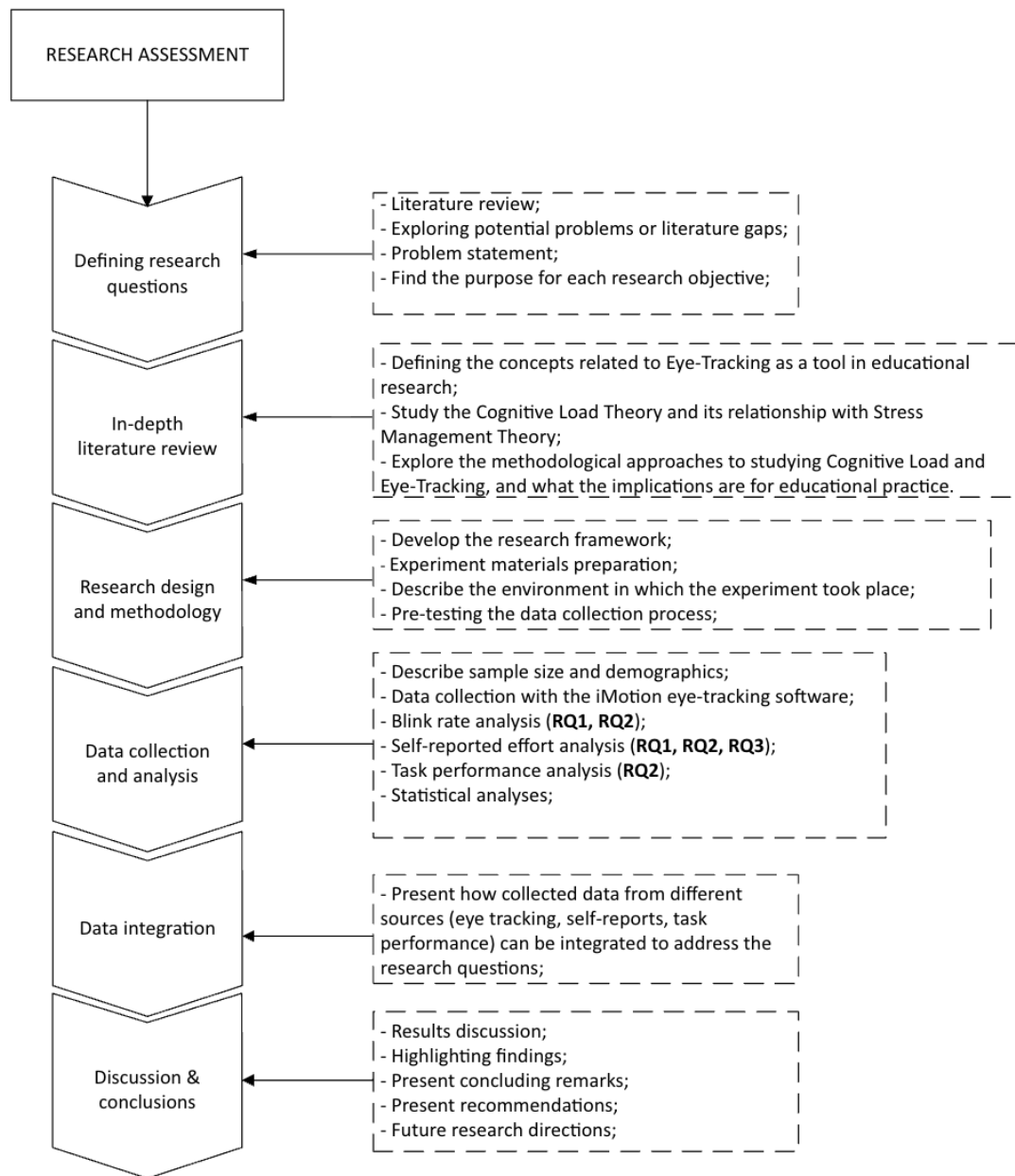


Figure 1. Research methodology framework

Source: Authors' own research.

The methodological framework of this study comprised two topics, and the learning materials were presented in three formats: text, graphics, and video. The learning materials used in the study consisted of three types of stimuli (Figure 2), an assessment question (the fourth stimulus in Table 1), and a question assessing preference for a particular learning material, which was considered the easiest task in terms of cognitive effort.

The first stimulus was the graphic variant, which used infographic diagrams; the second, the text variant, consisting of a descriptive explanation, and the third was a 90-second animated video. The easy phase involved passive content evaluation, and the hard phase required

comprehension assessment. The assessment phase included a multiple-choice question with four possible options and a single correct answer.

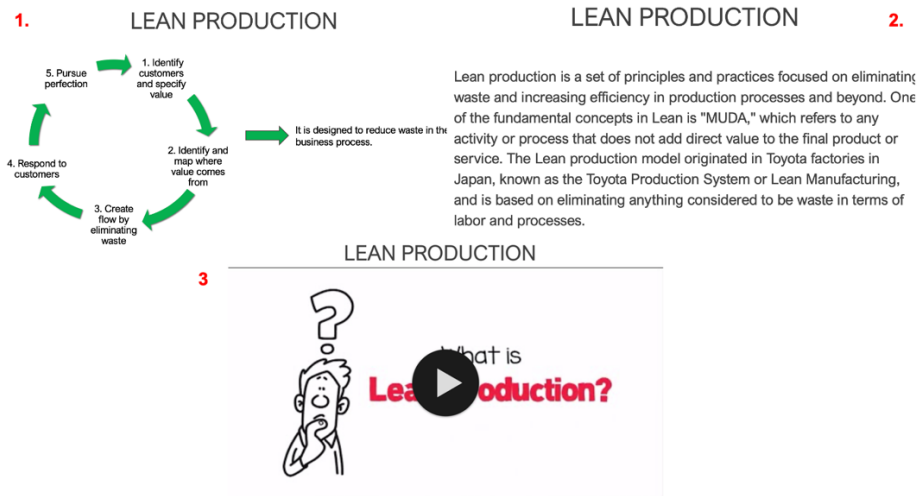


Figure 2. Learning materials used in the eye-tracking study

Based on Sweller's (2019) classification, Table 1 presents the learning stimuli used in the study, organised by cognitive load categories.

Table 1. Cognitive Load Components Associated with Each Type of Learning Stimulus

Stimuli	Type of learning material	Intrinsic load (task complexity)	Extraneous load (instructional design)	Germane load (reasoning)
Simulus 1	Graphics	Moderate	Visual	High – Visuals with moderate complexity usually support deeper processing if well designed; learners can focus cognitive resources on meaningful schema building.
Simulus 2	Text	Hard	Visual	Moderate – High intrinsic complexity in a text-only format can reduce germane load because working memory is heavily occupied with decoding and comprehension.
Simulus 3	Video	Low	Visual and audio	Low–Moderate – Low intrinsic load means that the material is easy; learners do not need to invest much additional cognitive effort to form new schemas. However, dual channels (visual + audio) can still engage in some germane processing if the design supports integration.
Simulus 4	Assessment	Hard	Visual	High – Even though the task is complex, assessments typically stimulate active retrieval and self-monitoring, promoting schema consolidation (i.e., high germane effort despite difficulty).

Source: Authors' own research.

Results and discussions

In the following section, we present the main results of the research and how these results relate to the research questions.

At the beginning of the experiment, the eye-tracking device was calibrated, and the distance between each student and the screen was approximately 50 cm. Both tasks were structured as follows: viewing the three learning formats, answering an assessment question, and rating the effort for each format. Participants were classified according to the alignment of the declared learning style (ILS) with gaze behaviour: visual styles (visual, sensing, active, global) with an expected preference for graphic and video learning materials, and verbal styles (verbal, intuitive, reflective, sequential) with an expected preference for text learning materials.

Three blink-related variables were considered in this study. Blink rate during high-demand tasks (BlinkRate_Hard). This measure captures the physiological response to high cognitive load conditions. In this case, the assessment question pertains to Stimulus 4 in Table 1. Blink rate during low-demand tasks (BlinkRate_Easy), the question assessing the presentation of the learning materials, and the blink rate differential (BlinkRate_Difference). A difference score was computed by subtracting the blink rate during low-demand tasks from the blink rate during high-demand tasks. This measure represents the individual's physiological reactivity to increased cognitive demands, controlling for baseline blink frequency. Positive values indicate elevated blink rate under cognitive load, while negative values suggest suppression.

We also considered subjective ratings of cognitive effort. Subjective cognitive effort evaluations were collected using self-report measures. Participants rated their perceived mental effort on a 7-point Likert scale (1 = very low effort, 7 = very high effort) for the three learning tasks: text-based content – Stimulus 1 (Effort_Text), graphical content – Stimulus 2 (Effort_Graphic), and video-based content – Stimulus 3 (Effort_Video). Table 2 presents the descriptive statistics for all the measured variables.

Table 2. Cognitive Load Components Associated with Each Type of Learning Stimulus

Variable	Mean value	Standard deviation	Min value	Max value
<i>Physiological Indicators</i>				
BlinkRate_Hard	10.68	5.94	0.00	22.28
BlinkRate_Easy	8.88	5.80	0.00	21.10
BlinkRate_Difference	1.81	5.99	-9.42	14.27
<i>Subjective Effort Ratings</i>				
Effort_Text	4.43	0.97	2.00	6.00
Effort_Graphic	5.40	0.77	4.00	7.00
Effort_Video	5.07	1.28	3.00	7.00

Source: Authors' own research.

Table 3 presents the correlation matrix between the blink-rate indicators described above and the subjective cognitive effort scores for the three learning materials.

Table 3. Correlations between Blink Rate Indicators and Subjective Cognitive Effort Ratings

Variable	Effort_text	Effort_graphic	Effort_video	Effort_Total
BlinkRate_Hard	- 0.180	- 0.157	- 0.011	- 0.106
BlinkRate_Easy	- 0.159	- 0.028	0.078	- 0.007
BlinkRate_Difference	0.023	- 0.151	- 0.057	- 0.094

Source: Authors' own research.

According to the values in Table 3, no correlation reached statistical significance at $|p| < 0.05$. Contrary to theoretical expectations derived from cognitive load theory, correlational analysis revealed consistently weak, nonsignificant associations between physiological blink rate measures and subjective effort evaluations. The correlation coefficients ranged from $p = -0.180$ to $p = 0.078$, with all p-values exceeding the conventional significance threshold of 0.05. The absence of significant correlations suggests the following facts: (a) blink rate and subjective effort represent partially independent dimensions of the cognitive load, (b) the relationship is moderated by individual variables not captured in the study, or (c) the sample size provided insufficient statistical information to detect small-to-medium effect sizes. To respond to RQ1, we further investigated whether individual differences in learning style preferences moderate the relationship between physiological and subjective indicators of cognitive load. To achieve this, the visual learning style was selected as the moderator based on sufficient variance in the present sample (70% of students were visual learners, $n = 21$; 30% were non-visual learners, $n = 9$). A multiple regression analysis was conducted with subjective effort for video content (Efort_Video) as the dependent variable. Table 4 presents the results of the moderated regression analysis.

Table 4. Regression Analysis Predicting Subjective Effort for Video Content

Predictor	Regression coefficient β	Standard Error - SE	t – statistic (β/SE)	p - value
Constant	1.893	1.382	1.369	0.183
BlinkRate_Hard	0.307	0.131	2.352	0.027*
Visual_Style	3.521	1.474	2.389	0.025*
BlinkRate_Hard $\times$ Visual_Style	-0.336	0.137	-2.462	0.021*

Source: Authors' own research

The interaction was statistically significant ($\beta = -0.336$, $SE = 0.137$, $t = -2.462$, $p = 0.021$), indicating that visual learning style moderates the relationship between blink rate and subjective effort for video content. A regression coefficient of 0.336 for non-visuals indicates that each 1-blink/minute increase in BlinkRate_Hard is associated with a 0.307-point increase in perceived effort for video. For visuals, this relationship is almost cancelled ($0.307 - 0.336 \approx 0$). The observed interaction admits that visual learners may process video-based content more efficiently than non-visual learners. Non-visual learners, faced with content that mismatches their preferred processing modality, may demonstrate superior calibration between physiological conditions and metacognitive monitoring. The relationship between blink rate as a physiological indicator and subjective assessments of cognitive effort is characterised by dissociation at the aggregate level and uncertain convergence at the individual level. This pattern aligns with the principles of Stress Management Theory (Rachmad, 2022), which posits that cognitive load is not uniform across individuals performing the same tasks but varies systematically with personal characteristics. The two types of measurement are complementary, and their correspondence depends on the individual characteristics of the learner, basically on the style of information processing. Rachmad (2022) recommends a multimodal evaluation combining physiological data with self-reports. To answer RQ1, this finding suggests that interpreting physiological indicators in educational contexts cannot be valid without accounting for individual differences that moderate the relationship between physiological variables and the subjective experience of cognitive effort.

Visual learning style is a significant moderator ($p = 0.021$) of the relationship between blink rate and perceived cognitive effort, whereas the type of educational content serves as a contextual

factor that defines the conditions under which this moderation manifests. These findings for RQ2 emphasise that a single coefficient cannot characterise the relationship between objective physiological measures and subjective assessments; rather, this relationship must be understood as conditioned by individual and contextual factors present in the learning situation. For future research, this implies considering models that explicitly integrate subjects' individual differences as moderators of the validity of physiological indicators, such as blink rate.

The results suggest that to develop learning-adaptive systems based on the observation of certain physiological indicators, one must adopt a more holistic approach, integrating individual calibration and contextualisation according to the type of content. For answering RQ3, adaptive learning systems cannot assume a direct correspondence between physiological indicators and subjective cognitive state without individualised validation. The moderating effect was identified specifically for video content, not for text or graphics. This contextual specificity implies that adaptive systems must employ different algorithms for each content type. The partial dissociation between physiological and subjective measures suggests that they capture complementary dimensions of cognitive load. Adaptive systems may benefit from integrating both sources of information. The correlations identified in this study suggest that integrating blink rate into adaptive learning systems is feasible but contingent. The added value of physiological monitoring lies in its ability to provide continuous, non-invasive detection; however, this value is realised only within an architecture that explicitly recognises individual heterogeneity, contextual specificity, and the complementarity between physiological measurements and subjective assessments as sources of information about cognitive load.

Conclusion

The present study investigated the relationship between blink rate, a physiological indicator, and subjective evaluations of cognitive effort during educational processing, with particular attention to individual and contextual factors that may influence this relationship. From this analysis, we have identified the following three findings.

First, the blink rate from the eye-tracking experiment and the subjective assessment showed statistically non-significant associations across all content types. This indicates that physiological and subjective measures of cognitive load do not automatically converge but appear to capture partially distinct dimensions of the cognitive load construct. This finding challenges the implicit assumption in much of the educational neuroscience literature that objective physiological indicators can serve as direct proxies for subjective cognitive experience.

Second, visual learning style was a statistically significant moderator of the relationship between blink rate and subjective effort for video-based content ($\beta = -0.336$, $SE = 0.137$, $t = -2.462$, $p = 0.021$). From this interaction, we can infer that non-visual learners showed a positive association between blink rate and perceived effort ($\beta = 0.307$), whereas visual learners showed a near-zero association ($\beta = -0.029$).

Third, the moderating effect described above depended on context, being present only for video-based content and not for text or graphical content. This underscores the importance of considering content display when interpreting physiological signals in educational settings.

Following Rachmad's (2022) framework, which emphasises that "continuous evaluation and strategy adjustments based on individual feedback are essential to ensure long-term success", an initial investment in learner profiling and calibration is needed for efficient cognitive load management. Although such personalisation means additional implementation costs, the alternative of having suboptimal training outcomes or potential learner disengagement is even more

undesirable. Organisations seeking a return on investment from physiological monitoring technologies need to consider, in addition to budgeting for hardware and software, investing in individual calibration protocols that transform raw physiological data into valid indicators of cognitive load. Educational managers should not rely on single-indicator cognitive load systems, as blink rate is unreliable across contexts. It is advisable to use individual calibration protocols. As revealed by our moderation findings, the effectiveness of these individual calibration protocols depends on individual characteristics and material type.

The study's limitations are also due to the sample size. A sample size of 30 participants may be sufficient for detecting large effects, but it provides limited statistical power to detect small-to-medium effects. The non-visual learner subgroup ($n = 9$) was particularly small, interpreting effect estimates for this group as potentially unstable. The significant interaction effect ($p = 0.021$), although below the conventional threshold, should be interpreted with a certain caution, given the sample constraints and the absence of correction for multiple comparisons. For future research, the study could be replicated with larger samples ($n > 100$) and a balanced representation of the learning styles groups. Field studies in real educational settings can establish the validity of these research findings and identify other contextual factors that may influence the physiological-subjective relationship.

Acknowledgements

The authors acknowledge that during the preparation of the manuscript, they used ChatGPT Plus as a support tool for structuring the research content. The authors have carefully reviewed all generated information to align with the research objectives of the present study. Also, Grammarly was used to support the English proofreading and improve the clarity of the manuscript. The authors assume full responsibility for the final content, interpretations and conclusions of the study.

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