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Facial Expression Analysis in Computer-Assisted Learning Environments During Reading and Problem-Solving Processes

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Abstract

This study aims to analyze students' facial expressions during reading and problem-solving tasks in a computer-assisted learning environment, focusing on their relationship with gender, academic performance, and time. Due to its exploratory nature, the research was conducted using a single-group post-test design. The study group consisted of 40 university students (23 female and 17 male). Participants were asked to read a scientific text and then solve a multiple-choice test. During the task, students' facial expressions were recorded through the computer's webcam and analyzed in real-time by a facial expression recognition algorithm measuring valence, arousal, and intensity. The collected data were analyzed using t-tests and regression analysis. Female students exhibited lower valence and higher intensity in their facial expressions compared to male students. No significant relationship was found between facial expressions and academic performance or reading duration. However, valence levels were observed to decrease as problem-solving time increased. These findings contribute to the literature on emotional state analysis in educational settings.

Keywords: Computer-assisted learning, reading comprehension, facial expressions, emotional and cognitive processes in education

Bilgisayar Destekli Öğrenme Ortamlarında Okuma ve Problem Çözme Süreçlerinde Yüz İfadesi Analizi

Öz

Bu çalışma, bilgisayar destekli bir öğrenme ortamında öğrencilerin okuma ve problem çözme süreçlerindeki yüz ifadelerini analiz ederek bu ifadelerin cinsiyet, başarı ve zaman değişkenleriyle ilişkisini incelemeyi amaçlamaktadır. Araştırma, keşfedici niteliği nedeniyle tek gruplu son test desenine göre yürütülmüştür. Çalışma grubunu 23 kadın ve 17 erkek olmak üzere toplam 40 üniversite öğrencisi oluşturmaktadır. Katılımcılardan bilimsel bir metni okumaları ve ardından çoktan seçmeli bir testi çözmeleri istenmiştir. Uygulama sırasında bilgisayarın kamerası aracılığıyla öğrencilerin yüz ifadeleri, yüz ifadelerindeki değerlik, uyarılma ve yoğunluk parametrelerini gerçek zamanlı olarak analiz eden bir görüntü işleme algoritmasıyla değerlendirilmiştir. Elde edilen veriler t-testi ve regresyon analizleriyle çözümlenmiştir. Kadın öğrencilerin yüz ifadelerinde erkeklere göre daha düşük değerlik ve daha yüksek yoğunluk değerleri gözlenmiştir. Yüz ifadeleri ile başarı ve okuma süresi arasında anlamlı bir ilişki saptanmamıştır. Ancak, problem çözme süresi uzadıkça yüz ifadelerindeki değerlik düzeylerinin azaldığı bulunmuştur. Elde edilen bulgular, eğitimde duygusal durumların değerlendirilmesine yönelik literatüre katkı sağlamaktadır.

Anahtar kelimeler: Bilgisayar destekli öğrenme, okuduğunu anlama, yüz ifadeleri, eğitimde duygusal ve bilişsel süreçler

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INTRODUCTION

Learning is a complex structure intertwined with affective processes, transcending being a purely cognitive operation. Specifically, while reading and problem-solving can trigger various emotional responses in learners, learners' existing emotional states directly shape reading, meaning-making, and problem-solving skills (Pekrun, 2022). The process of text reading can lead to intense emotional fluctuations in the reader, and these emotions profoundly influence the quality of learning from the text. In particular, academic emotions are not static; they change dynamically over time in response to the content of the text, its difficulty level, and other learning tasks. This dynamic structure becomes evident when the text becomes too difficult or too easy for the reader, or at moments when conceptual barriers create "cognitive disequilibrium" (Graesser & D'Mello, 2012). In an increasingly digitalized world, reading in computer-assisted learning environments elicits psychophysiological responses that differ from those elicited by reading printed materials. Text type (scientific vs. personal) and topic constitute key determinants of the emotional and cognitive shifts observed in this process (Mason et al., 2018). In addition, individual differences in working memory (Laskay-Horváth et al., 2025), readers' attitudes toward the text, and beliefs related to the text type or topic constitute key determinants of these shifts (Gregory, 2004). According to Martucci et al. (2025), facial expressions in reading comprehension tasks are indicators of students' emotional engagement and performance. In this context, identifying readers' affective states such as boredom, frustration, or confusion and managing them strategically holds substantial promise for enhancing reading comprehension.

Computer-assisted learning environments offer undeniable advantages, such as access independent of time and place. At the same time, they face core challenges, including limited interaction and inadequate affective feedback (Xiao, 2017). In traditional face-to-face settings, teachers can observe students' gestures, facial expressions, and body movements to interpret affective states such as boredom, fatigue, enjoyment, or satisfaction in real time and adjust the flow of instruction through timely interventions. In contexts where interaction unfolds naturally, students' behavioral and cognitive engagement directly supports academic achievement. In contrast, in online learning environments, educators' access to such vital cues is constrained (Rucks-Ahidiana, 2014). At present, assessments of achievement and motivation in computer-assisted environments are typically conducted using post-hoc instruments, such as surveys or short quizzes. Although these tools can provide information related to behavioral and cognitive engagement, they offer limited insight into affective engagement, which is inherently momentary and dynamic (Han et al., 2024; Prayogo et al., 2024). Prayogo (2024) emphasizes that sustaining affective engagement in such contexts requires the establishment of real-time feedback mechanisms that capture learners' emotional states, which is essential for the sustainability and quality of education. Accordingly, there is a clear need in distance education for systems that can mitigate students' sense of isolation while using the screen and embed forms of "emotional intelligence" into instructional delivery.

Although self-report measures are frequently used in the literature to identify emotional processes, such as epistemic emotion scales (Pekrun et al., 2017) and PANAS (Watson et al., 1988), Graesser and D'Mello (2012) argue that emotions experienced during reading are most accurately assessed through the recording of physiological responses, the measurement of brain activity, and the analysis of facial expressions. Accordingly, indicators such as respiratory sinus arrhythmia (Daley et al., 2014), electroencephalography (EEG), and eye-tracking technologies (Cheng et al., 2020) are commonly employed as objective measurement tools in reading comprehension tasks. Among these physiological indicators, facial expressions stand out as one of the strongest and most natural cues through which individuals externalize their affective states (Fida et al., 2023). Although facial expressions can generally be deliberately regulated, micro-expressions that emerge during processes requiring interest, attention, and intensive cognitive activity are considered involuntary physiological reactions (Ekman, 1993; Sharma et al., 2020). Recent advances in image processing, machine learning, and deep learning algorithms have enabled the detection and interpretation of these expressions in real time using standard webcams (Dever et al., 2022; Stolba et al., 2024; Zhang & Wang, 2024).

Although recent studies have focused on detecting students' boredom and fatigue in online environments through facial expressions (Xu et al., 2023; Zhang & Wang, 2024), research that uses facial expressions as a predictor of higher-order cognitive processes, such as reading comprehension remains an emerging area (Turan et al., 2022), within the learning analytics literature, facial expressions can provide critical information not only about learners' affective states but also about the underlying dynamics of cognitive processing (Ahn & Harley, 2020). According to Pekrun (2011), achievement emotions are grounded in individuals' appraisals of control and value during learning activities, and are expressed through physiological channels, such as facial behavior. In the present study, valence represents the degree of satisfaction, arousal reflects the level of physiological activation, and

intensity captures the strength of the emotion. Accordingly, the primary aim of this study is to analyze students' affective states in computer-assisted learning environments by using webcam-based image processing technologies to derive emotion-related indicators from facial expressions during a reading task, and to examine the predictive effect of these indicators on reading comprehension performance. The study seeks to contribute to the literature by proposing a technological approach to mitigate the lack of interaction in distance education and by providing empirical evidence on how affective data can be incorporated into instructional design.

Emotions and Learning

While the positive effects of emotions on learning are frequently emphasized in research, maintaining a consistently positive atmosphere throughout the learning process remains a challenge. Learning content can sometimes be engaging and motivating, while at other times it may appear dull and focused on rote memorization. Additionally, assignments or problem-solving activities given after learning tasks can lead to dissatisfaction and anxiety. Studies have shown that students' emotions influence several important learning outcomes, such as school dropout (Ekornes, 2022), self-regulation (You & Kang, 2014), motivation (Artino, 2009b), satisfaction (Artino, 2009a), academic achievement (Niculescu et al., 2015; Ruthig et al., 2008), and reading and comprehension processes, which are the focus of this study (Ainley et al., 2002, 2005). These findings highlight the need to consider students' emotional and affective experiences in course design (Jena, 2019; Moreno & Mayer, 2007).

Pekrun's (2006) control-value theory suggests that achievement-related emotions arise from two key appraisals: control (the extent to which students feel they can influence outcomes) and value (the perceived importance of the learning activity). Within this framework, a student who perceives high value but has a low sense of control may experience anxiety. In contrast, a student with low value perception and high control may feel boredom. Achievement emotions can be categorized along three dimensions: valence (positive/negative), activation (activating/inhibiting), and object focus (past, present, future). For example, the enjoyment felt during a well-prepared presentation can be classified as a positive-valence, high-activation, and present-focused emotion (Pekrun, 2011). Generally, while positive emotions tend to have beneficial effects on learning, negative emotions are not always detrimental. For instance, Artino (Artino, 2009a) suggested that frustration might enhance metacognitive processes, leading students to invest additional cognitive resources to improve comprehension.

Most studies focus predominantly on achievement and epistemic emotions, while social emotions are often overlooked. This is mainly because much research examines student-computer interactions rather than student-student interactions. In this context, various methods are used, such as online observations, emotional think-aloud protocols, video analysis, facial expression tracking, and galvanic skin response measurements (D'Mello, 2013). This study, however, investigates the relationship between emotional states in facial expressions and cognitive processes such as reading and reading comprehension.

There are a few studies focused on interpreting facial expressions related to learning and comprehension processes. Among the few studies in this field, Turan et al. (2018) and Turan et al. (2022) highlight the promise of real-time data on emotional states during cognitive processes such as reading comprehension. In their 2022 study, Turan et al. employed an innovative method called Event-Related Intensities (ERI), which refers to changes in the intensity of facial configurations elicited by specific events. Using this method, they examined changes in participants' facial expressions in response to correct and incorrect statements and the feedback they received. The findings demonstrated that facial dynamics are promising not only for understanding emotional processes but also for comprehending cognitive processes, such as understanding. In this context, our study's results will provide valuable insights into how cognitive processes such as reading and comprehension are reflected in facial expressions.

Measurement of Facial Expressions

According to Ekman's (1993) findings, there are seven basic facial expressions universally present across all races and cultures. These are neutral, happy, surprised, fearful, angry, disgusted, and sad expressions. Ekman and Friesen (1978) developed the Facial Action Coding System (FACS) to categorize facial expressions based on action units (AUs). AUs are anatomically linked to the contraction of specific facial muscles. They can occur individually or in combination. AU combinations can be additive, in which case the combination does not alter the appearance of the individual components, or non-additive, in which case the appearance of the components changes. Although the number of anatomical action units is relatively small (only 44), more than 7,000 combinations of action units have been observed (Scherer & Ekman, 1982). These combinations of facial movements can be effectively utilized in facial expression analysis through two-dimensional geometric feature variations. These dimensional changes enable facial expressions to be represented within a two-dimensional polar space (Russell, 1980).

Russell's dimensional affect model incorporates the seven basic emotions within a circular model centered on neutrality, assuming a two-dimensional polar affective space along the arousal-valence axis (Figure 1).

In this study, to measure changes in facial expressions during reading and problem-solving tasks, the effective facial expression analysis method proposed by Vonikakis and Winkler (2021) was employed. This method uses geometric features for dimensional affect recognition. Russell's (1980) approach was established as a dimensional affect model, offering an alternative to Ekman and Friesen's (1971) categorical model.

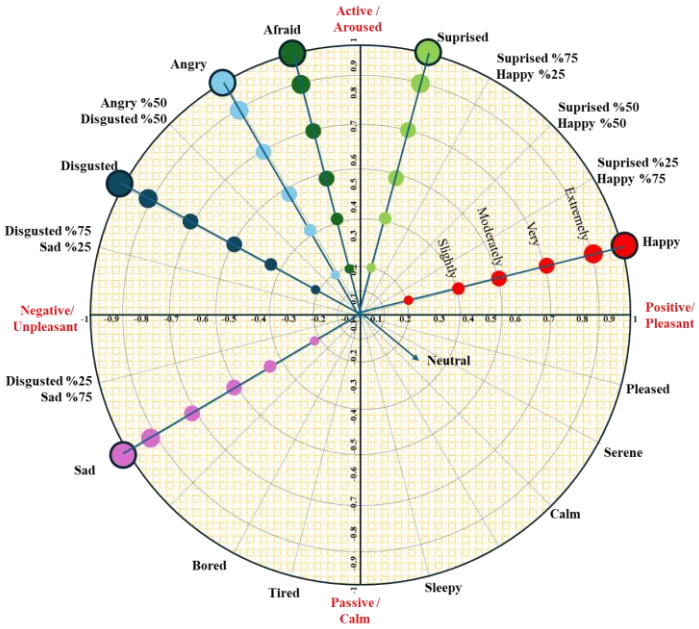


Figure 1. Two-dimensional polar affective space adapted from Vonikakis and Winkler (2021)

The distance from the center (i.e., deviation from neutrality) represents the mild, moderate, high, and very high intensity of facial expressions. Very high-intensity expressions (e.g., extremely happy) are positioned on the outer edge of the emotional space. In contrast, low-intensity expressions (e.g., slightly happy) are located closer to the center, near the neutral point. Figure 1 illustrates such an emotional space. Arousal and valence are scaled within the range of [−1, 1]. Emotions are defined by angles within the [0°, 360°] range, while the intensity of the expression is determined by its distance from the center (Neutral) and is scaled between [0, 1].

Valence and arousal are easily associated with specific functions of distinct brain regions. The right hemisphere's parietal region appears to play a particular role in mediating arousal, whereas the frontal regions are observed to have a specific role in emotional valence (Kollias & Zafeiriou, 2021).

Research Questions

The primary aim of this study is to examine the relationships among affective state data derived from students' facial expressions (valence, arousal, and intensity) and academic achievement, task completion time, and gender during reading and problem-solving processes in computer-assisted learning environments. Accordingly, the study sought to answer the following research questions:

1. Do participants' facial expressions during the reading process significantly differ by gender?
2. Do participants' facial expressions during the problem-solving process significantly differ by gender?
3. What is the relationship between participants' facial expressions during the reading process and their achievement test scores?
4. What is the relationship between participants' facial expressions during the problem-solving process and their achievement test scores?
5. What is the relationship between participants' facial expressions during the reading process and their reading durations?
6. What is the relationship between participants' facial expressions during the problem-solving process and their problem-solving durations?

The study's hypotheses were developed based on Pekrun's(2006) Control-Value Theory and prior research on affective signal processing. According to Pekrun (2011), achievement emotions are grounded in individuals' perceptions of control and value during learning activities, and these emotions are expressed through

physiological channels such as facial expressions. In this study, valence represents the level of satisfaction, arousal reflects the degree of physiological activation, and intensity denotes the strength of the emotion. The expected relationships among the study variables are presented below, together with their theoretical rationale.

Gender and Emotional Expression

A substantial body of research suggests that gender is a salient factor shaping emotional expressiveness and the intensity of facial behavior. Prior work reports that, compared with men, women tend to express their emotional states more actively through facial expressions and may exhibit distinct affective responses during cognitive activities such as reading (Brody & Hall, 2008). From this perspective, gender is expected to be associated with differences in the emotion parameters derived from facial expressions (valence, arousal, intensity).

H1: Participants' facial-expression parameters (valence, arousal, intensity) during the reading process differ significantly by gender.

H2: Participants' facial-expression parameters (valence, arousal, intensity) during the problem-solving process differ significantly by gender.

Facial Expressions and Academic Achievement

According to Control Value Theory, positive emotions, characterized by higher valence, typically facilitate deeper learning by enhancing cognitive flexibility. In contrast, negative emotions, such as boredom or excessive anxiety, can impair performance by depleting attentional resources (Pekrun et al., 2017). Facial expressions serve as immediate indicators of these internal affective states, for instance, brow furrowing may signal cognitive effort or confusion. Therefore, facial expression patterns observed during reading and problem-solving, including markers of satisfaction or stress, are expected to predict final achievement test scores.

H3: There is a significant relationship between participants' facial-expression parameters during the reading process and achievement test scores.

H4: There is a significant relationship between participants' facial-expression parameters during the problem-solving process and achievement test scores.

Facial Expressions and Cognitive Processing Time

During states of cognitive disequilibrium, such as when a text becomes more difficult or a problem cannot be solved, students' facial expressions (e.g., surprise, heightened focus, boredom) often show noticeable shifts, which typically coincide with longer processing times (Graesser & D'Mello, 2012). By contrast, a student who is in a state of flow or who comprehends the material with ease is expected to display more neutral or positive facial expressions and to complete the task within a more optimal time frame. Accordingly, changes in facial expression parameters are expected to correlate with the time spent on the task.

H5: There is a significant relationship between participants' facial-expression parameters during the reading process and reading time.

H6: There is a significant relationship between participants' facial-expression parameters during the problem-solving process and problem-solving time.

The hypothesis diagram developed in line with the research questions and the theoretical framework is presented in Figure 2. In this model, participants' momentary affective states are conceptualized through three core psychophysiological parameters: (1) Valence, which characterizes an individual's level of satisfaction or dissatisfaction; (2) Arousal, which reflects the physiological dimension of emotion and the degree of activation versus deactivation in response to a stimulus; and (3) Intensity, which captures the dominance or strength of the experienced emotion along a continuum from low to very high. The study aims to test the relationships among these parameters and gender, academic achievement, and cognitive processing time.

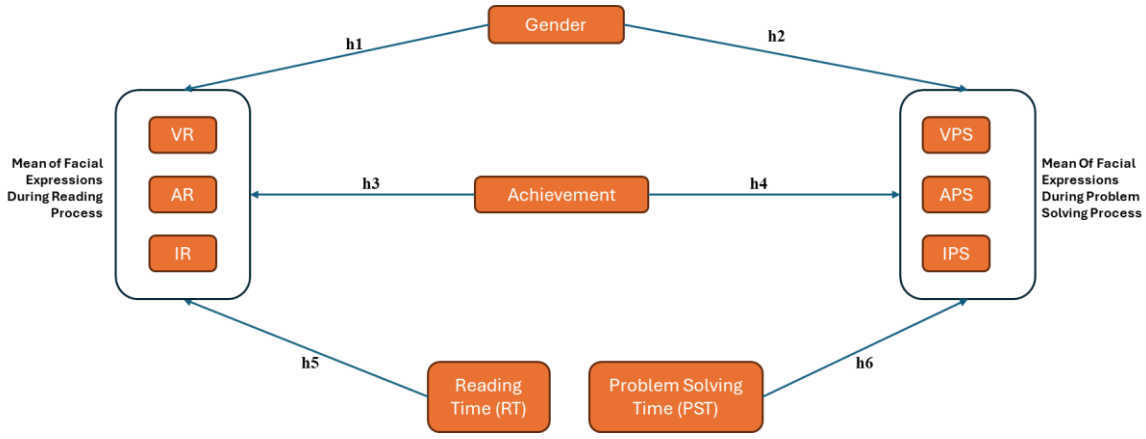


Figure 2. *Hypothesis diagram*

In the model depicted in Figure 2, the abbreviations denote the mean affective values derived from webcam-captured facial expressions during the reading and problem-solving tasks, along with the corresponding process variables. The operational definitions of the codes used in the diagram are specified below.

Reading process variables: VR (valence-reading), AR (arousal-reading), and IR (intensity-reading) refer to the mean affective parameters during the reading activity, whereas RT denotes the total reading time in seconds.

Problem-solving process variables: VPS (valence-problem solving), APS (arousal-problem solving), and IPS (intensity-problem solving) refer to the mean affective parameters during the problem-solving phase, whereas PST denotes the problem-solving time in seconds.

Outcome variable: In the model, achievement represents the number of correct responses on the assessment test administered at the end of the process.

During the analysis, the statistical validity of each alternative hypothesis specified in the diagram (H1 through H6) was tested against the corresponding null hypotheses.

METHOD

Research Design

Due to the exploratory nature of the study, a one-group posttest-only design was employed (Creswell & Creswell, 2017). The primary objective was to examine the relationships between facial expressions and cognitive processes during specific tasks. Despite certain limitations in causality and external validity inherent in this design (Gray, 2004), it facilitated data collection within a focused, controlled experimental environment. Given the complexity of facial behaviors, this exploratory approach allowed for nuanced observations necessary for hypothesis generation (Barrett et al., 2019).

Participants

The sample for this study consisted of 40 university students (23 females and 17 males) aged 18 to 23. The participants consisted of students enrolled in the Department of Turkish Language and Literature within the Faculty of Arts and Sciences. The sample selection aimed to ensure homogeneity in terms of verbal proficiency and text-analysis skills across participants' fields of study. Participants were invited to the application laboratory at specific times and voluntarily participated after being informed about the study.

Tools

Reading Text and Achievement Test

In this study, participants were asked to read an informational text about the malaria parasite's mosquito host (HHMI, 2013b) and human host (HHMI, 2013a), prepared by the Howard Hughes Medical Institute and translated into Turkish by the researchers. Following the reading task, a recall test developed by Dindar (2015) was administered to assess participants' knowledge of the malaria life cycle. This multiple-choice test consisted of 18 questions, and its KR-20 internal consistency coefficient was calculated as 0.61. This result is acceptable, as noted by Schmitt (1996). The purpose of administering this achievement test was to evaluate participants' ability

to predict the topics covered in the reading text. Indeed, several studies have used the same topic and achievement test for different purposes (Dindar & Akbulut, 2016; Dönmez & Akbulut, 2021; Mercimek et al., 2020; Örün & Akbulut, 2019). In the study by Dönmez and Akbulut (2021), the test's internal consistency coefficient was calculated as 0.68. Although 0.70 is often cited in the literature as a general threshold for reliability, many authors consider 0.60 acceptable, particularly for group comparisons or teacher-developed tests. In the present study, the internal consistency coefficient obtained for the achievement test was 0.78. DeVellis (2012) characterizes reliability coefficients in the 0.60 to 0.65 range as "minimally acceptable"; nevertheless, he notes that 0.60 may be used as a practical threshold in applied research.

Algorithm

During the reading of the text and the problem-solving tasks, participants' facial expressions were recorded using a facial expression function developed in Python 3.6. This application collected 12 data points per second for valence, arousal, and intensity. Since 3 data points were recorded every 0.25 seconds, a total of 12 per second were collected for each parameter.

For example, if the database contains 1,200 data points during the reading process, this corresponds to a 100-second reading duration. Similarly, if the database contains 2,400 data points for the problem-solving process, this indicates a problem-solving duration of 200 seconds.

In the analysis, the average valence, arousal, and intensity values recorded during the reading and problem-solving processes were used.

To implement a two-dimensional approach for facial expression analysis, a novel data augmentation/conversion method was employed. This method transforms categorical emotion datasets into dimensional datasets by automatically generating valence, arousal, and intensity annotations (Figure 3).

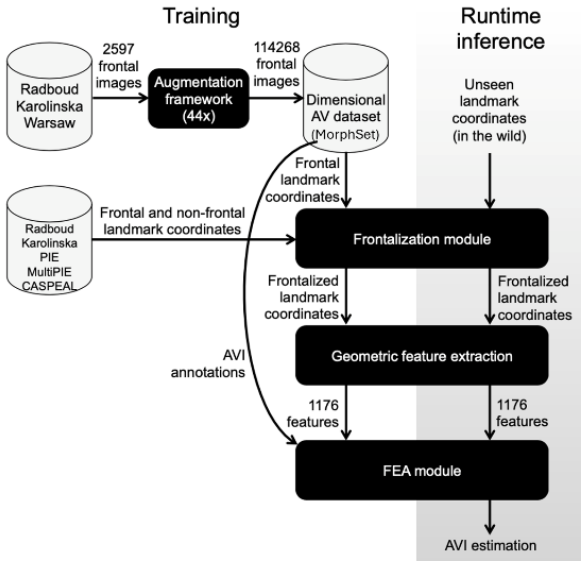


Figure 3. Facial expression extraction module (Vonikakis & Winkler, 2021)

The approach provides a 44x augmentation factor. Three datasets containing a total of 2,597 original categorical images were combined (Goeleven et al., 2008; Langner et al., 2010; Olszanowski et al., 2015), resulting in a dataset with 114,268 training images.

To correct for variations in head posture, a landmark-based frontalisation technique was also applied. For this purpose, the frontalisation module was trained using five different datasets (D'Mello & Graesser, 2010; Gao et al., 2008; Goeleven et al., 2008; Langner et al., 2010; Rasouli et al., 2019). This frontalisation module flattens head movements, converting them into a direct frontal view (Figure 4).

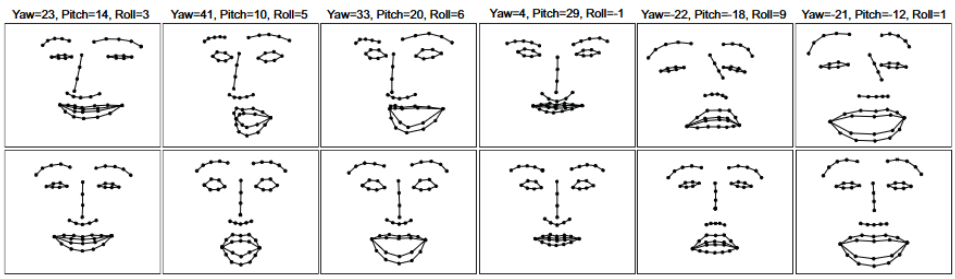


Figure 4. Frontalisation (Vonikakis & Winkler, 2020)

Facial pose is expressed in a 3D space using yaw, pitch, and roll values (Patrick, 2023). Yaw represents rotation around the z-axis, pitch refers to rotation around the y-axis, and roll indicates rotation around the x-axis. The frontalisation module in the facial expression function corrects for different head rotation angles to align facial expressions with a frontal view, accurately capturing their valence, arousal, and intensity values (Vonikakis & Winkler, 2020). This ensures that during the reading and problem-solving tasks, the participant's facial expression parameters—valence, arousal, and intensity—can be easily detected, even when the participant's head is tilted at various angles.

In their study, Vonikakis and Winkler (2021) used several methods to predict valence, arousal, and intensity parameters, including Multi-Layer Perceptron (MLP), Principal Components Regression (PCR), Random Forest Regression (RF), and Ridge Regression. The lowest Mean Squared Error (MSE) results they obtained were 0.0367 for valence, 0.0276 for arousal, and 0.0235 for intensity.

The facial expression function developed in Python 3.6, predicted valence, arousal, and intensity values for new facial data using the trained model and frontalisation algorithm from the facial expression extraction module shown in Figure 5. Once the participant sat at the computer and initiated the task, the Python-based application simultaneously launched the reading text and the facial expression function.

The function recorded data every 0.25 seconds, continuously saving facial expression values into a database during the reading and problem-solving processes. The algorithm did not record video; instead, it processed live images in real time and stored the numerical values in the database for analysis.

Data Collection

This research offers valuable insights into the role of facial expressions in online learning environments and serves as a foundation for future studies with more rigorous designs. The data collection process of the study is illustrated in Figure 5.

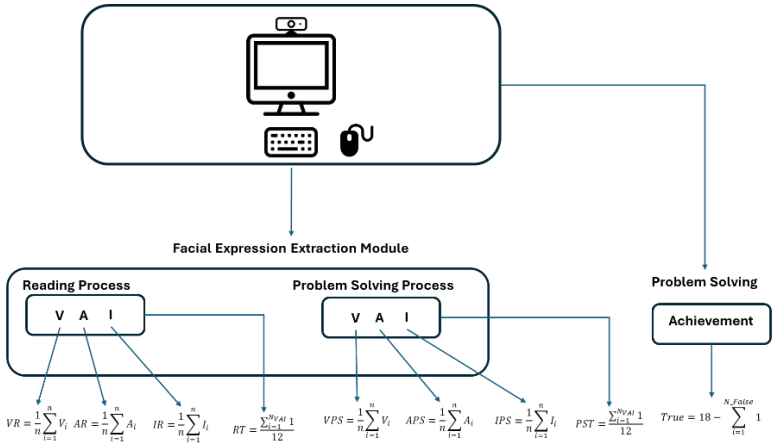


Figure 5. Data collection process

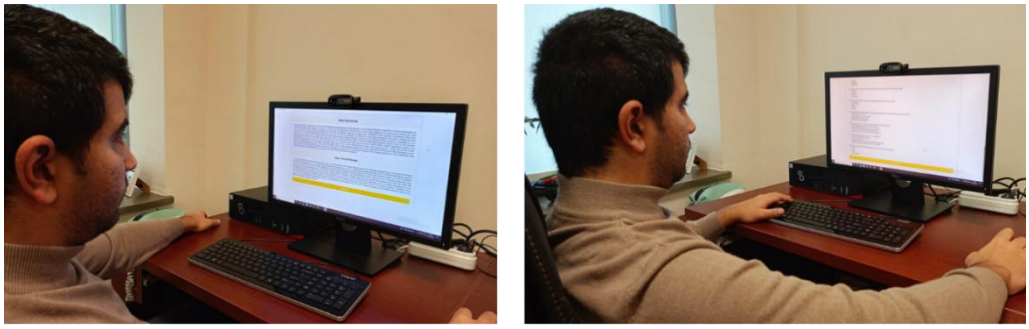
In the study, the facial expression extraction module collected real-time data from the camera during the reading and problem-solving processes. The values for VR (Valence during Reading), AR (Arousal during Reading), IR (Intensity during Reading), VPS (Valence during Problem-Solving), APS (Arousal during Problem-Solving), and IPS (Intensity during Problem-Solving) were calculated by taking the arithmetic mean of the raw data.

Data Analysis

The quantitative data were analyzed using SPSS software. Independent-samples t-tests were conducted to examine gender differences in facial expression parameters. Multiple linear regression analyses were employed to investigate the relationships between facial expressions (valence, arousal, intensity), academic performance scores, and task durations during reading and problem-solving phases.

Process

The application was conducted using a computer equipped with an Intel Core i5-9400 @2.9GHz processor, 8GB of memory, and a 21.5-inch, 60Hz monitor. The reading screen was operated at a 1920x1080 resolution. An external Logitech C270 camera with 720p resolution and 30 fps was connected to the computer. An example of the application's reading and problem-solving processes is presented in Figure 6.



a) Reading Process b) Problem Solving Process

Figure 6. Reading and problem-solving processes.

During the reading process (Figure 6-a), participants read a text describing the malaria parasite's hosts in mosquitoes and humans. The problem-solving process (Figure 6-b) began immediately after the reading task. In this stage, participants answered questions related to the topic. In both processes, the camera remained active, and the algorithm continuously recorded real-time data on participants' facial expression parameters into the database. The achievement test scores were recorded in the database after participants completed the problem-solving tasks.

Prior to implementation, participants also provided informed consent indicating their agreement to the capture of facial expression data via webcam. No video recordings were taken during the implementation. The algorithm stored the student identifier, the process type (reading or problem-solving), and the facial expression parameters valence, arousal, and intensity in the database. Within the scope of the research questions, the variables of interest were the facial expression parameters (valence, arousal, and intensity), the achievement score, and the time spent on reading and problem-solving. For each participant, gender, mean facial expression values during the reading and problem-solving phases, reading time, problem-solving time, and achievement test scores were compiled in SPSS. Descriptive statistics for all participants, including the mean, standard deviation, kurtosis, skewness, and Shapiro–Wilk p values, are presented in Table 1.

Table 1. Descriptive Statistics of the Data

Type of Variables	Variables	Mean	Sd	Skewness	Kurtosis	Shapiro-Wilk (p)
Facial Expressions	VR	-0.144	0.15	-0.355	0.905	0.735
	AR	0.183	0.087	-0.153	-0.077	0.625
	IR	0.312	0.088	0.877	1.118	0.058
	VPS	-0.167	0.17	0.213	0.141	0.328
	APS	0.181	0.08502	-0.338	-0.521	0.201
	IPS	0.34	0.085	0.602	0.606	0.207
Time	RT	213.625	57.671	0.696	0.693	0.070
	PST	376.5	123.589	-0.596	0.0526	0.190
Points	Achievement	10.275	1.811	0.302	0.186	0.735

In Table 1, the variables VR, AR, and IR represent the valence, arousal, and intensity values of facial expressions during the reading process. In contrast, VPS, APS, and IPS represent the valence, arousal, and intensity values during the problem-solving process. The variable RT denotes reading time, and PST denotes problem-solving time. The achievement variable indicates the number of correct answers obtained from the 18-question achievement test.

The suitability of the data for statistical analysis was comprehensively assessed using analytical tests. Given that the sample size was below 50 (N = 40), the Shapiro–Wilk test was used as the primary assessment of normality. Its results were supported by the skewness and kurtosis coefficients (Mishra et al., 2019). As shown in Table 1, the skewness and kurtosis values for the facial-expression parameters and time variables fall within the ±1.5 range, indicating an approximate normal distribution (Tabachnick & Fidell, 2006). In addition, the Shapiro–Wilk test yielded p values above the conventional significance level for all variables ($p > .05$), thereby supporting the assumption of normality.

Research Ethics

Ethical approval for the study was granted by the Scientific Research and Publication Ethics Committee of the Rectorate of Kırklareli University, with the decision numbered E-35523585-199-166136.

FINDINGS

The findings obtained in relation to the research questions are presented below:

Findings Related to Research Question 1

To answer Research Question 1, an independent samples t-test was conducted to examine differences in facial expression values by gender during reading. The results of the t-test are presented in Table 2.

Table 2. Differences in the Mean Values of Facial Expressions During the Reading Process Between Female and Male Participants

Variable	Female		Male		t	p	Cohen's d	Levene	
	Mean	Ss	Mean	Ss				F	p
VR	-.207	.142	-.058	.115	3.541	.001*	.132	.056	.458
AR	.182	.086	.184	.091	.045	.963	.088	.001	.980
IR	.343	.0931	.270	.063	-2.762	.008*	.0819	.896	.350

*p<.05

The analyses of the valence (VR), arousal (AR), and intensity (IR) variables during the reading process, presented in Table 2, reveal that facial expressions differ by gender in their emotional responses. The lower mean valence score among female participants compared to male participants indicates that women showed more negative emotional reflections in their faces. This difference was statistically significant ($p < 0.05$), though the effect size was small (Cohen's $d = 0.13$). In terms of intensity (IR), women's facial expressions reflected more intense emotional reactions, and this difference was also statistically significant ($p < 0.05$) but with a limited effect size (Cohen's $d = 0.08$). However, no significant difference in arousal (AR) was found between female and male participants, with both groups exhibiting similar responses ($p > 0.05$). The Levene's test results indicate that the variances are homogeneous ($p > 0.05$). In conclusion, while minor gender-based differences were observed in valence and intensity of facial expressions, no distinct difference in arousal levels was identified between genders.

Findings Related to Research Question 2

To address Research Question 2, an independent-samples t-test was conducted to examine differences in facial expression values by gender during the problem-solving process. The t-test results are presented in Table 3.

Table 3. Differences in the Mean Values of Facial Expressions During the Problem-Solving Process Between Female and Male Participants

Variable	Female		Male		t	p	Cohen's d	Levene	
	Mean	Sd	Mean	Sd				F	p
VPS	-.224	.133	-.088	.186	2.689	.01*	.158	3.203	.081
APS	.174	.076	.191	.096	.637	.527	.085	2.492	.123
IPS	.350	.087	.087	.082	-.902	.372	.085	.040	.842

*p<.05.

The analyses of the valence (VPS), arousal (APS), and intensity (IPS) variables during the problem-solving process, presented in Table 3, reveal that facial expressions differ by gender in terms of emotional responses. Female participants exhibited more negative emotional reflections in terms of valence (VPS) than male participants, and this difference was statistically significant ($p < 0.05$), although the effect size was small (Cohen's $d = 0.16$). Regarding intensity (IPS), women's facial expressions reflected more intense emotional reactions, but this difference was not statistically significant ($p > 0.05$) and had a limited effect size (Cohen's $d = 0.09$). No significant difference was observed between female and male participants in the arousal (APS) variable, with both groups displaying similar emotional responses ($p > 0.05$). The Levene's test results indicate that the variances are homogeneous ($p > 0.05$). In conclusion, while a significant difference in valence was observed in facial expressions during the problem-solving process, no notable gender-based differences were detected in intensity and arousal levels.

Based on the findings for Research Questions 1 and 2, significant gender differences were observed in the facial-expression measures of valence, arousal, and intensity during both the reading and problem-solving tasks. Specifically, across the reading and problem-solving phases, female participants exhibited more negative facial expressions than male participants, falling within the disgust-to-anger range. The intensity of these expressions was also higher among females than among males. Male participants, in contrast, more frequently displayed facial expressions corresponding to fear. Although males showed higher arousal values than females, this difference was not statistically significant (Figure 7).

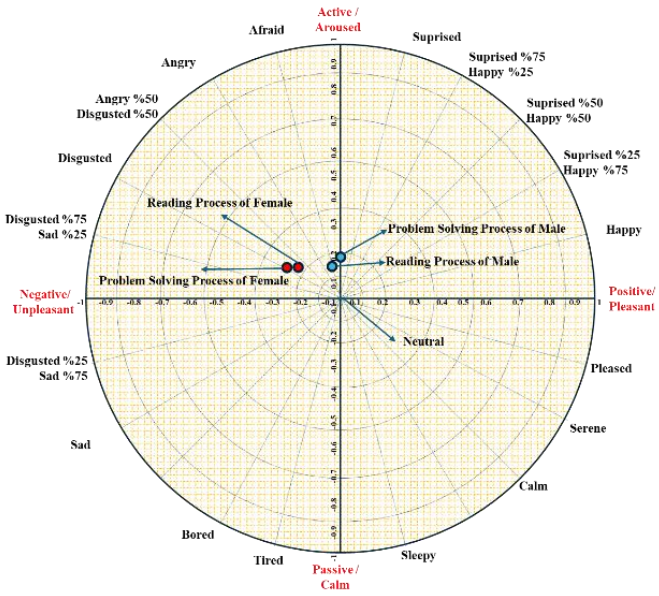


Figure 7. Representation of female and male participants' facial expressions in the two-dimensional polar affective space during reading and problem-solving processes

As illustrated in Figure 7, female participants' facial expressions during the problem-solving phase were more negative than those observed during the reading phase. This pattern suggests that women adopted a more serious facial expression while solving problems than when reading. By contrast, during problem-solving, male participants' facial expressions shifted toward the positive range compared with reading, and their arousal levels increased. Overall, while males displayed more positive facial-expression states during problem solving than during reading, females exhibited an increase in negative facial expressions.

Findings Related to Research Question 3

To answer Research Question 3, a regression analysis was conducted to examine the relationship between participants' mean facial expression values during the reading process and their achievement test scores. The results of the regression analysis are presented in Table 4.

Table 4. Regression Results Between Facial Expressions During the Reading Process and Achievement Test Scores

	Coefficient (B)	Standard Error	t	p
VR	4.204	3.372	1.247	.221
AR	-5.680	4.904	-1.158	.254
IR	4.039	5.348	.755	.455

Table 4 shows that the regression analysis revealed no statistically significant effects of the valence (DO), arousal (UO), and intensity (YO) variables on academic performance scores during the reading process ($p > 0.05$). While the valence and intensity variables had positive effects ($B = 4.204$ and $B = 4.039$), the arousal variable had an adverse effect ($B = -5.680$). However, since none of these effects were statistically significant, it was concluded that these variables do not make a meaningful contribution to predicting academic performance.

Findings Related to Research Question 4

To address Research Question 4, a regression analysis was conducted to examine the relationship between participants' mean facial expressions during the problem-solving process and their achievement test scores. The regression analysis findings are presented in Table 5.

Table 5. Regression Results Between Facial Expressions During the Problem-Solving Process and Achievement Test Scores

	Coefficient (B)	Standard Error	t	p
VPS	2.898	2.569	1.128	.267
APS	-3.409	-.160	-.717	.478
IPS	1.671	.079	.379	.707

The analysis results presented in Table 5 indicate that the effects of the VPS (Valence during Problem-Solving), APS (Arousal during Problem-Solving), and IPS (Intensity during Problem-Solving) variables on achievement scores are not statistically significant. While the valence and intensity variables showed positive relationships with achievement scores, the arousal variable showed a negative relationship. However, the high p-values ($p > 0.05$) suggest that these variables do not significantly predict achievement. These findings imply that the emotional variables during the problem-solving process do not have a meaningful impact on performance, and other factors may play a more critical role in determining success.

Findings Related to Research Question 5

To answer Research Question 5, a regression analysis was conducted to examine the relationship between participants' mean facial expression values during reading and their reading durations. The results of the regression analysis are presented in Table 6.

Table 6. Regression Results Between Facial Expressions During the Reading Process and Reading Durations

	Coefficient (B)	Standard Error	t	p
VR	-34.322	109.907	-.312	.757
AR	17.089	159.830	.107	.915
IR	-57.608	174.280	-.331	.743

The regression analysis results presented in Table 6 examine the relationships between valence (VR), arousal (AR), and intensity (IR) variables during the reading process and the participants' reading durations. The results indicate that none of these variables show a statistically significant relationship with reading duration ($p > 0.05$). Negative relationships were observed between valence (VR) and intensity (IR) and reading duration ($B = -34.322$ and $B = -57.608$, respectively), while a positive relationship was observed between arousal (AR) and reading duration ($B = 17.089$). However, none of these relationships were statistically significant, as indicated by the high p-values (VR: $p = 0.757$; AR: $p = 0.915$; IR: $p = 0.743$). These results suggest that the relationships between these variables and reading duration are weak and coincidental. In conclusion, other factors should be considered to understand better the factors influencing reading duration.

Findings Related to Research Question 6

To answer Research Question 6, a regression analysis was conducted to examine the relationship between participants' mean facial expressions during the problem-solving process and their problem-solving durations. The results of the regression analysis are presented in Table 7.

Table 7. Regression Results on the Effect of Facial Expressions During the Problem-Solving Process on Problem-Solving Duration

	Coefficient (B)	Standard Error	t	p
VPS	171.382	160.205	1.070	.292
APS	-791.650	296.357	-2.671	.011*
IPS	87.581	274.736	.319	.752

**p<.05*

According to the regression results presented in Table 7, arousal (APS) in facial expressions has a significant effect on problem-solving durations ($p < 0.05$) and shows a negative relationship. This indicates that higher levels of arousal are associated with shorter problem-solving durations. However, the valence (VPS) and intensity (IPS) variables in facial expressions do not have a statistically significant effect on problem-solving duration ($p > 0.05$). These findings suggest that problem-solving duration is more strongly linked to arousal levels, while other facial expression measurements are not decisive in this process.

In the present study, no significant association was observed between reading time and facial-expression measures. However, as the problem-solving duration increased, the arousal values derived from facial expressions tended to shift in a negative direction. Accordingly, a negative relationship was identified between problem-solving time and the arousal indicator (APS) (Figure 8).

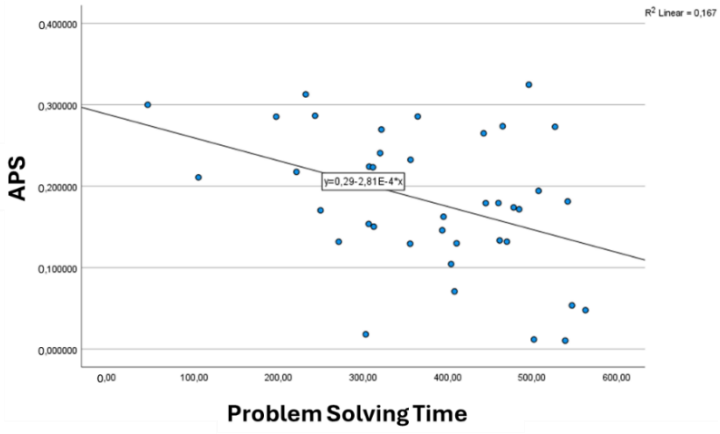


Figure 8. Relationship between facial arousal levels and problem-solving duration

As shown in Figure 8, arousal values derived from facial expressions decreased as problem-solving time increased. This pattern may indicate a decline in arousal and a concomitant reduction in attentional focus. It may also suggest that prolonged cognitive processing is associated with negative changes in facial-expression indicators. However, negative emotions can yield different outcomes within learning contexts.

Based on analyses of all research questions, some of the proposed hypotheses were supported. A detailed representation of the findings in the hypothesis diagram is provided in Figure 9.

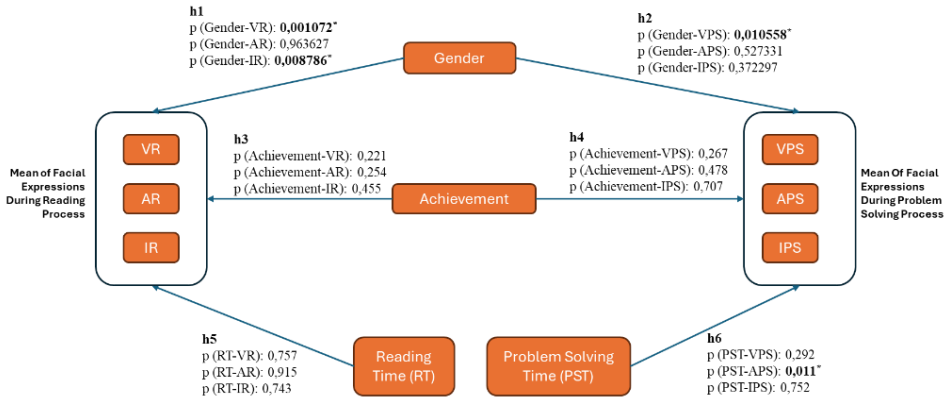


Figure 9. Hypothesis results

The research findings revealed significant differences in specific facial expression parameters during reading and problem-solving, supporting our H1 and H2 hypotheses. On the other hand, no significant relationship was observed between the achievement variable and the durations of reading and problem-solving. Therefore, our H3 and H4 hypotheses were not supported. Similarly, the H5 hypothesis, which posited a relationship between reading duration and facial expressions, was not supported by the lack of significant findings. However, a significant relationship was found between problem-solving duration and facial expressions, thus supporting our H6 hypothesis.

DISCUSSION & CONCLUSION

Detecting various emotional states from students' facial expressions in educational settings is beneficial for providing real-time feedback on the effectiveness of lesson sessions (Chickerur & Joshi, 2015; Zhang & Wang, 2024). Such feedback can offer insights into students' typically weaker emotional engagement in online learning environments (Fida et al., 2023). Moreover, information about individuals' emotional states can provide clues about their cognitive processes (Hopwood et al., 2024; Zhang et al., 2024). In this context, the real-time analysis of learners' emotional states in online learning environments is key to designing deliberate interventions that enhance the effectiveness of learning settings (Grafsgaard et al., 2013; Han et al., 2024; Prayogo et al., 2024). This study examined facial expression dynamics to predict emotional states during reading and problem-solving processes. During each computer-assisted task, participants' facial valence, arousal, and intensity data were collected via the camera.

When the dimensional facial expression data collected during the reading and problem-solving tasks were examined by gender, a clear divergence was observed (see Figure 7). Female participants' expressions remained

predominantly negative and at higher intensity levels throughout the process, whereas male participants' expressions shifted toward the positive range. The study by Zhang et al. supports these findings. (2024), which suggests that women exhibit more negative emotions than men during cognitive tasks. Zhang et al. (2024) also found that men are less emotionally reactive to cognitive challenges. For women, increased anger may reflect higher levels of stress or frustration due to cognitive demands. According to Zhang et al. (2024), women tend to experience greater anxiety in competitive learning environments, which they attribute to excessive cognitive load. Similarly, Ainley (2002, 2005) emphasized that personal interest in a text significantly influences comprehension and the decision to continue reading, although external factors also play a critical role. Women's emotional reactivity in learning environments may indicate greater affective engagement (Zhang et al., 2024), potentially manifesting as greater , and an effort to focus on less engaging texts. The more negative valence in women's facial expressions compared to men's in this study may stem from this persistent engagement.

In light of these findings, the first and second research questions, along with the corresponding hypotheses (H1 and H2), were supported. Our results align with prior work, including Brody and Hall (2008), which emphasizes gender as a salient determinant of emotional expressiveness and the intensity of facial behavior. The observation that women displayed more intense, more negatively valanced facial expressions (ranging from anger to disgust) than men during cognitively demanding activities such as reading and problem-solving is consistent with the theoretical expectation that women are more likely to externalize affective states through facial expressions. Accordingly, gender was found to be a meaningful source of variation in affective signal processing.

Our study did not find a significant relationship between the achievement variable and facial expressions during reading and problem-solving tasks. According to the Control-Value Theory, actions perceived as beyond learners' control can lead to negative emotions such as anxiety and anger (Pekrun & Linnenbrink-Garcia, 2014). Similarly, Hopwood et al. (2024) found that students' emotions during cognitive processes vary across three engagement profiles (Whizz, Worker, Worrier). The Worrier profile tends to feel comfortable and confident only when processes are under their control, but experiences stress when faced with uncontrollable or evaluative tasks. This may explain why achievement scores were not significantly related to facial expressions during reading and problem-solving. Emotional states linked to facial expressions in cognitive tasks may be influenced more by students' engagement profiles and control-value perceptions than by achievement itself.

In this context, the answers to the third and fourth research questions indicated, contrary to expectations, that there was no statistically significant relationship between facial-expression measures and academic achievement scores; therefore, hypotheses H3 and H4 were not supported. Pekrun's (2006; 2017) Control Value Theory generally posits that positive emotions facilitate deeper learning and thereby enhance performance, whereas negative emotions tend to undermine performance. However, the absence of the expected association in the present study suggests a mismatch between the temporal characteristics of the measures: facial expressions reflect momentary, phasic physiological responses, whereas the achievement test captures a cumulative cognitive outcome. In other words, participants' immediate expressions of stress or satisfaction did not emerge as a sufficient standalone predictor of final achievement.

The analysis results indicate that the effect of cognitive task duration on facial expression measures varies by task type (see Figure 8). Unlike reading time, longer problem-solving duration was associated with a significant decrease in facial-expression-based arousal (APS), yielding a negative correlation. According to Ahn and Harley (2020), students with a negative emotional profile tend to achieve the highest learning gains. Negative emotions reflected in facial expressions can serve as indicators of cognitive focus and mental engagement. In this regard, the negative valance values observed during longer problem-solving tasks in this study suggest that participants were intensely focused and mentally engaged in cognitive processing. Similarly, Kumar et al. (2024) noted that positive facial expressions are associated with creative thinking, whereas negative facial expressions reflect critical thinking. Therefore, the negative facial expressions observed during the problem-solving process in this study could be interpreted as signs of an intensive critical thinking process.

Regarding the time variables, no significant relationship was found for the fifth research question (reading time), and thus H5 was rejected. In contrast, significant relationships were identified for the sixth research question (problem-solving time), providing support for H6. This pattern may be interpreted through D'Mello and Graesser's (2010; 2012) concept of cognitive disequilibrium. Whereas the reading phase unfolded as a relatively fluent and affectively neutral process for participants, the problem-solving phase emerged as a period characterized by cognitive strain and disequilibrium, during which more pronounced shifts in facial-expression indicators (e.g., decreased arousal and more negative valence) were associated with longer processing time. Overall, the extent to

which facial expression changes correlate with task duration appears to differ as a function of task difficulty and task demands (reading versus problem-solving).

On the other hand, some studies link students' enjoyment of the learning process with their academic success (Hopwood et al., 2024; Pekrun et al., 2002). Hopwood et al. (2024) found that extending cognitive processes affects emotional states differently depending on students' engagement profiles. Successful students classified as "Whizz" perceive challenges in learning as opportunities for deep thinking and improving solutions, leading to emotions such as joy, curiosity, or satisfaction during prolonged engagement. However, Hascher (2010) noted that students' satisfaction with their own performance and learning can diminish over time. Therefore, the increasing intensity of negative facial expressions observed during extended problem-solving tasks in this study may reflect a more general pattern rather than being solely influenced by participants' engagement profiles.

Recommendations

The findings of this study indicate that gender-based differences in affective expressiveness constitute a critical indicator for monitoring cognitive processes. To address the lack of face-to-face interaction and real-time feedback in online learning environments, integrating emotion-recognition systems that analyze facial expressions in real time is recommended. In this regard, the Facial Expression Extraction Module used in the present study (Vonikakis & Winkler, 2021), along with similar open-source algorithms, supports the feasibility of implementing such systems in a cost-effective and accessible manner using standard hardware. This type of integration would enable educators to monitor learners' momentary affective states during demanding tasks, such as problem-solving (e.g., stress, sustained attention), thereby facilitating the personalization of instructional strategies and timely pedagogical interventions. Future research may further contribute to the design of more responsive online learning environments by leveraging accessible machine-learning models to examine complex affective patterns.

Limitations

Although our study did not find a significant relationship between reading comprehension and facial expressions, future research should explore the inclusion of advanced machine learning models to analyze complex emotional patterns and investigate their impact on learning outcomes across various online learning environments. These efforts could contribute to the development of more responsive and engaging online learning environments. Some of the non-significant results in our study may be attributed to certain limitations. The primary reason for selecting a scientific text was to capture facial expressions related to reading comprehension rather than emotional responses to the text. However, texts that are more interesting and personally valuable are more easily understood (Ainley et al., 2002, 2005). Therefore, future research aiming to determine the relationship between reading comprehension and facial expressions could involve texts that participants find personally engaging and valuable. Moreover, while facial expressions provide instantaneous data, emotions related to reading comprehension and learning may require participants to experience a longer process. Although participants were informed about the experimental procedures before the application, their complete lack of prior knowledge of the text and the absence of a preliminary study may have led to uncertainty during the reading process.

Additionally, the short length of the reading text used in the application (412 words) may not have provided enough opportunity for participants to familiarize themselves with the content or to engage with the topic thoroughly. This might have limited the ability to detect a significant relationship between reading duration and facial expressions. Therefore, future studies could involve longer educational reading texts related to participants' familiar fields to allow for more comprehensive observation of the process. Furthermore, the data in this study were limited by the capabilities of the webcam and algorithm used in the data collection tools. With advancements in technology, the use of higher-quality cameras and more sophisticated algorithms could enable more detailed analysis of facial expressions and yield more robust analytical outcomes.

Statements of Publication Ethics

We affirm that we did not submit this manuscript to another journal.

Researchers' Contribution Rate

Authors	Literature review	Method	Data Collection	Data Analysis	Results	Conclusion
Author 1	☒	☒	☒	☒	☒	☒
Author 2	☒	☐	☐	☐	☒	☒

Conflict of Interest

We acknowledge the absence of any conflicts of interest or ethical issues.

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