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Facial Expression Recognition for Investigating Attention and Affective States in Synchronous Online Higher Education

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Abstract

This study aims to identify students' emotions and attention levels in live online classes through image processing technologies employed in the field of affective computing, as well as to reveal the factors influencing students' emotions. To achieve this goal, the Emotion and Attention Tracking System (EATS) platform was developed. Another objective is to determine the predictive capacity of the data obtained through the EATS platform. Within the scope of the study, an explanatory sequential design under the mixed-methods research framework was adopted. The sample consisted of 40 undergraduate and graduate students. Data were collected through EATS records, questionnaires, observation forms, and semi-structured interview forms. For the analysis of the data, descriptive analysis, paired-samples t-tests, and content analysis methods were employed. Findings indicate that the EATS platform reliably and accurately measures emotions such as surprise, sadness, anger, fear, disgust, happiness, neutrality, as well as attention levels. However, it was also found that fatigue and other highly complex emotional states (emotions too intricate to be resolved) were measured with a higher margin of error, indicating lower reliability. Moreover, the factors influencing students' emotions during live online sessions were found to be primarily related to the instructor (e.g., behavior, tone of voice, communication skills, technical competence). Additionally, students' emotions were also affected by peers, the environment from which they connected to the class, and technical problems encountered during the session. Overall, EATS demonstrates a high level of accuracy in detecting students' emotions. Such platforms, employing diverse affective computing methods, can serve as effective tools for identifying students' emotional and attentional states. Consequently, providing real-time feedback based on students' emotional conditions in online learning environments can enhance the effectiveness of teaching processes and foster greater student engagement.

Keywords: Distance Education, Live Lecture, Affective Computing, Image Processing Technology, Emotion and Attention Tracking System (EATS), Higher Education

Introduction

Distance education plays a significant role in addressing various educational problems and enhancing the quality of teaching and learning processes. One of the major contributions of distance education is preventing students from being deprived of educational opportunities due to economic reasons, thereby promoting equal access to education (Aksu & Cantürk, 2015; Engelbrecht, 2005). Moreover, the elimination of time and space constraints fosters the development of the concept of “anytime and anywhere learning,” offering advantages such as study flexibility and lifelong learning (Oliveira et al., 2018; Kır & Bozkurt, 2020). On the other hand, despite these advantages, distance education environments also pose several challenges. These challenges include the inability to identify students’ emotions (Wang & Lin, 2018), the difficulty in determining students’ satisfaction levels (Lin et al., 2016), the emergence of certain emotional deficiencies (Li et al., 2008), a decline in students’ motivation (Leontidis et al., 2008), and reduced efficiency in educational processes (Iulamanova et al., 2021). In the literature, several strategies have been proposed to address these difficulties: developing and using systems that identify students’ emotions (Wang & Lin, 2018; Li et al., 2008), determining satisfaction or motivation levels based on the frequency of positive and negative emotions (Lin et al., 2016), creating motivational materials for individuals identified with low motivation (Leontidis et al., 2008), and conducting emotion assessments to provide emotional support when inefficiencies arise due to emotional problems (Iulamanova et al., 2021). Within this framework, the present study addresses the process of identifying learners’ emotions in line with the core approaches of the field of affective computing.

Literature Background

Emotion and Attention

Emotion can be defined as a state that arises in response to an external or internal stimulus (Scherer, 2000). Attention, on the other hand, is defined as the extent to which an individual focuses on a single thought among internally generated ideas, commonly known as mind-wandering (Seli et al., 2018). Experiencing positive emotions and maintaining high levels of attention are essential for quality teaching and learning processes (Rowe et al., 2015). Happy students complete their tasks more willingly and successfully (Hernik & Jaworska, 2018), whereas when they are unhappy, their motivation decreases. In education, affective computing aims to recognize and interpret students’ emotional states, personalize learning experiences, and adapt teaching strategies through real-time feedback, thereby providing a more effective, inclusive, participatory environment that supports student well-being (Das et al., 2025).

Defining and measuring the situations, emotions, and moods that affect individuals involves various challenges. It can be difficult to have individuals verbally state the emotions they are experiencing; however, when an emotion is felt, certain indicators emerge. Typically, the emotions felt by an individual are directly reflected in facial expressions, and in most cases, there is no reason to conceal them (Matsumoto et al., 2008). The literature provides reliable cues linking certain facial expressions to specific emotions (Matsumoto et al., 2008). For example, a happy person smiles by lifting the corners of the lips, and the eyes narrow slightly (Kaitz et al., 1988). If these indicators can be transferred to and processed by computer programs, emotions can be measured; the scientific field enabling the transformation of data obtained from individuals into emotions is known as affective computing (Picard, 2000). Nevertheless, difficulties in expressing emotions among individuals with autism or mood disorders may lead to inconsistencies in measurement (Baxter & Hobson, 2024). Therefore, while facial expressions provide valuable cues, they may not be sufficient on their own (Cernea & Kerren, 2015). To reduce uncertainty, the literature suggests conducting holistic analyses and emphasizes that more reliable results can be achieved by diversifying data sources (Scherer, 2005; Millard & Hole, 2008).

Data Sources Used in Emotion Measurement

Fifty years ago, emotions were primarily measured through observations based on psychological activities (Lang, 1969) and facial, hand, and body movements (Mehrabian, 1970). Today, however,

researchers employ diverse data sources that provide objective and quantitative insights to measure emotions more effectively. Physiological signal processing is a fundamental method, as it analyzes bodily signals such as heart rate and skin conductance (Khare et al., 2024). Facial recognition technology offers direct measurement of emotional states by examining facial expressions and subtle muscular changes (Canal et al., 2022). Wearable devices, such as smartwatches, enhance measurement accuracy by collecting physiological data, particularly in remote interactions (Khare et al., 2024). Speech pattern analysis identifies emotional cues by evaluating tone and vocal patterns (George & Muhamed Ilyas, 2024). Similarly, EEG signal processing provides another layer of understanding by analyzing brain activity to infer emotional states (Pillalamarri & Shanmugam, 2025). With technological advancements and the growing knowledge base in affective computing, it is now widely recognized that valid and reliable emotion measurement can be achieved by integrating three types of data sources: perception-based measures, physiological data, and self-reported data (Cernea & Kerren, 2015). The combined use of these three sources has been suggested in the literature as one of the most effective approaches.

Literature Review

One of the prominent approaches in distance education is the use of facial recognition technologies. Due to the security vulnerabilities of password-based systems, biometric solutions provide more reliable alternatives. A system developed in Iran demonstrated high accuracy (Farshchi & Toosizadeh, 2014), while a Moodle-integrated facial recognition tool was found to have higher acceptance rates in Latin America compared to Spain (Guillén-Gámez & García-Magariño, 2015). The European Union-funded TeSLA Project combined facial recognition with voice, keystroke dynamics, and plagiarism detection to offer multi-biometric verification (Guerrero-Roldán et al., 2020). More recently, deep learning-based models have further enhanced the accuracy of facial recognition, increasing efficiency in enrollment processes (Salamh & Akyüz, 2022).

In recent years, facial recognition technology has been employed not only for identity verification but also for analyzing students' behavior, attention, and emotions. For instance, students' behaviors during online learning were examined through video data (Xiang et al., 2024). By processing parameters such as facial, hand, and posture tracking to detect phone usage, attention levels were predicted with 99.75% accuracy using the XGBoost algorithm (Hossen & Uddin, 2023). Moreover, in systems designed for exam security, facial recognition was integrated with eye and mouth movement analysis, voice analysis, and user behaviors to identify suspicious cases (Jia & He, 2021). Multi-layered systems based on monitoring browser behaviors were shown to reduce cheating attempts and strengthen perceptions of academic integrity (Sakhipov et al., 2025). Facial recognition has also been applied to determine students' attendance in synchronous classes (Ozdemir & Ugur, 2021). An especially noteworthy application, the FILTWAM system, analyzed both voice tone and facial expressions to identify students' emotional states in real time, enabling the learning environment to be adapted accordingly (Bahreini et al., 2016).

Such studies on emotion analysis demonstrate the diversity of emotion measurement methods employed in the literature. Overall, image processing technologies have emerged as the most prominent approach. In this method, variables such as eyelid openness, lip width and openness, eyebrow height, and facial wrinkling are analyzed to infer emotional states from facial expressions (Lin et al., 2012; Su et al., 2016; Tung, 2013; Wang & Lin, 2018). From the moment individuals experience an emotion, noticeable changes occur in their facial expressions, thereby facilitating the detection of emotions (Tung, 2013). In addition to image processing methods, voice-based approaches have also gained importance; emotional states are calculated by analyzing tone, energy, and vocal expressions (Bahreini et al., 2016; McStay, 2020; Tung, 2013; Wu et al., 2016). Moreover, individuals' self-reports of their own emotions provide another valuable source of data, and numerous studies in the literature have utilized this method (Franěk et al., 2022; Ketonen et al., 2023). At a more advanced level, emotional states are also analyzed through physiological data sources. Parameters such as heart rate, brain electrical activity, skin conductance, blood oxygenation, and respiration have been used in emotion measurement (Akbiyik, 2010; Maldonado, 2018;

McStay, 2020; Williamson, 2017). However, it has been noted that the devices used in such methods can be bulky and potentially uncomfortable for individuals (Lin et al., 2014).

Rationale

Since self-report questionnaires rely on individuals' subjective perceptions, they may lead to misleading results (Murphy et al., 2003), while the high cost and error margins of biosignal measurement devices restrict their widespread use (Pekrun, 2006). Although questionnaires were the most commonly used method for emotion measurement between 2010 and 2023 (Yuvaraj et al., 2025), relying on a single data source is insufficient to capture the emotional fluctuations of students in a holistic manner. In affective computing, the measurability and reportability of emotions are strongly emphasized (Boehner et al., 2007), and the literature highlights the need to support these measurements with synchronous visual systems (Ez zaouia et al., 2020). As an accessible and cost-effective solution addressing these limitations, image-processing-based facial tracking has emerged as a promising approach. For example, a CNN-based Real-Time Facial Emotion Detection Application achieved 85% accuracy in recognizing emotions (Hakim et al., 2024), while the De Expression Residue Learning technique provided superior classification performance beyond that of single-method approaches in online learning contexts (Shan et al., 2024). These findings suggest that infrastructures utilizing camera-based systems, rather than biosignal devices, may offer both reliable and sustainable solutions for emotion recognition.

Significance

Monitoring students' emotions and attention levels in real time during live lectures not only ensures accurate perception but also allows for the immediate adaptation of teaching strategies. CNN–LSTM hybrid models have demonstrated high performance in providing real-time emotional feedback and detecting fluctuations in attention; for example, Cheng and Tang (2024) reported effective results using this approach. Similarly, single facial recognition systems integrated with MobileNet-v2 achieved 87% accuracy in classifying student participation, thereby improving engagement assessment (Eliyas, 2024).

Within this framework, the proposed Emotion and Attention Tracking System (TS) will integrate perception-based data extracted from facial expressions with students' subjective self-reports collected at the end of each lesson. This integration will enable real-time analysis and provide students with individualized evaluations of their emotional and cognitive states throughout the learning process. Accordingly, this research aims to develop EATS, to determine the extent to which the system accurately measures students' emotions, and to identify the factors influencing emotions and attention levels in live lecture environments. In line with these objectives, the study will seek to address the following research questions:

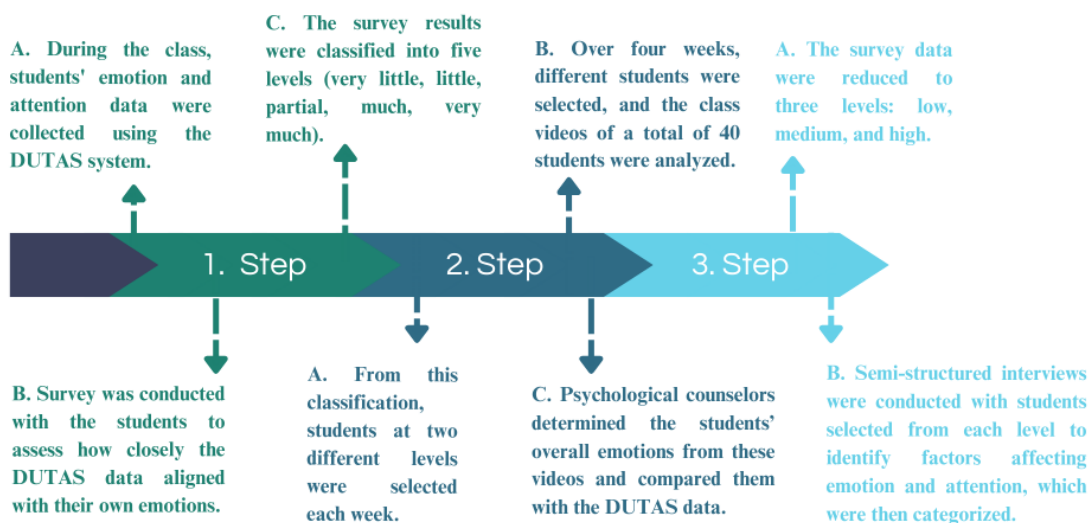
1. According to the data obtained from the EATS platform, are there significant changes in students' emotion and attention levels over time?
2. What is the degree of consistency between observational data and EATS measurements?
3. What are the underlying factors influencing the changes in students' emotion and attention levels during live lectures?

Method

A mixed-methods research design was employed in this study. Mixed-methods research enables the simultaneous use of both quantitative and qualitative approaches (Creswell, 2017). Such designs do not restrict researchers to traditional quantitative or qualitative methods alone; rather, they encourage the use of multiple approaches to provide more comprehensive answers to research questions (McMillan & Schumacher, 2013, p. 33). Studies utilizing mixed-methods designs allow one or more research questions to be fully addressed (Johnson & Onwuegbuzie, 2004). In this context, it can be stated that the mixed-methods design offers a more holistic perspective by integrating quantitative and qualitative

methods within a single study, thereby facilitating a deeper explanation of various aspects of the phenomenon under investigation (Davies, 2017).

Figure 1. Method



Quantitative Dimension

In the quantitative dimension of this mixed-methods study, surveys and expert evaluations were employed to determine how accurately emotion measurement methods, based on camera recordings in live lectures, captured students' emotions. Within the quantitative research process, a repeated-measures design under the framework of experimental research was utilized. Experimental research seeks to identify the extent to which variables are influenced and the conditions under which they change (McMillan & Schumacher, 2013, p. 29).

Qualitative Dimension

In the qualitative dimension of this study, a case study design was employed to explore the factors influencing students' emotions during live lectures. A case study is a qualitative research design that allows for the in-depth examination of a phenomenon (McMillan & Schumacher, 2013, p. 32).

Participants

The sample of the study consisted of 40 undergraduate students enrolled in a distance statistics course at the Faculty of Education, Atatürk University. During the course, students participated using devices such as laptops, mobile phones, and tablets. It was assumed that students who turned on their cameras participated voluntarily, and this was formalized through an informed consent form. Considering the limitations in physical access and reaching larger sample groups, a purposive sampling method was employed to select individuals who were knowledgeable about the subject and met specific criteria. To minimize participants' concerns, ethical approval was obtained from the relevant ethics committee prior to the study.

Demographic Information of Participants

In the initial weeks of the study, some participants were unable to continue due to various reasons, resulting in sample attrition. Consequently, the final quantitative research process included 40 students. Demographic data of the participants were collected through a questionnaire. Of these participants, 22 were female and 18 were male, with ages ranging from 19 to 27 years. Each week, in addition to the previous participants, 10 students were selected. For this selection, students were categorized into low, medium, and high achievement levels, ensuring that each weekly group included a minimum of two and a maximum of four students from each level. The classroom recordings of the selected students were systematically examined by expert evaluators according to predetermined criteria.

For the qualitative research process, students were selected from among the 10 participants included in the quantitative process each week, based on their self-reported perceptions of how accurately the system measured their emotions. These students were grouped into low, medium, and high perception levels, and one or two students were selected from each group, with a maximum of four interviews conducted per week. This method was designed to enhance sample diversity by incorporating the views of students with different perception levels. In total, 16 students participated in the qualitative research process, including 4 females and 12 males, with ages ranging from 19 to 27 years.

Data Collection Tools

Emotion and Attention Measurement Tool Using Image Processing Technology

In this study, the focus was on emotions defined in Ekman’s (1992) basic emotion theory—sad, happy, surprised, disgusted, angry, and fearful—along with the additional categories of tired, neutral, and other complex emotions. On the EATS platform, where live lectures were conducted, students’ emotional and attentional states were measured in real time through image processing technology for those who had their cameras activated. To identify students’ emotions and attention levels from their facial expressions, a face recognition–based system was employed. In this system, key facial features (e.g., eyes, nose, mouth, and ear regions) were detected as nodal points, and variations in the distances between these points were analyzed to label emotional states. Table 1 presents examples of facial movements and their corresponding icons on the EATS platform.

Table 1. Equivalent Visuals of Emotions and Attention Levels in the EATS Platform

Emotions	Happy	Sad	Surprised	Disgusted	Neutral	Angry	Scared	Tired	Other complex emotions	Attention level
DUTAS Icon									Other Facial Expressions	0  100
Sample Facial Expression									Not in listed categories	Based on face-to-screen angle

Student Emotion Assessment Questionnaire

At the end of each lecture, students evaluated the data collected through image processing using a questionnaire generated from their own results. In the questionnaires, the frequency counts of different emotions were separately measured and divided by the total frequency of emotions during the lecture to present percentage ratios (e.g., Neutral: 85%; Happy: 3%; Angry: 8%; Surprised: 6%). Students’ attention levels were also calculated by averaging facial expression–based measures throughout the lecture and were displayed in the questionnaire. Since each student demonstrated varying emotions and attention levels during the lecture, the data naturally differed from one individual to another. For example, in the first five minutes of a 40-minute lecture, Student X might display happiness, while Student Y might exhibit a neutral state; at the end of the lecture, their percentages would be reported with different distributions. Ultimately, each student’s emotional data were presented through a five-point Likert-type questionnaire, with the accuracy of the measurements left to students’ personal evaluations. The Likert scale ranged from 1 = Very Low, 2 = Low, 3 = Moderate, 4 = High, and 5 = Very High. An example of the questionnaire is provided in Figure 2.

Figure 2. *Personalized Survey*

How accurate do you think the data is?

Your attention level in the online course	Survey (A)
Average attention: 70.0000%	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Your emotional distribution in the online course	Survey (B)
Happy %9.259	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Fear %0.000	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Neutral %59.722	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Angry %0.000	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Surprised %12.037	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Tired %3.704	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Disgust %0.000	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Sad %0.000	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Other mixed emotions %15.278	☐ Not at all ☐ Low ☐ Partially ☐ High ☐ Very high
Submit	

Observation

To validate the findings obtained through image processing, an additional evaluation was conducted by independent observers. Psychological counselors reviewed students' behaviors during the lectures using video recordings and recorded the observed emotions with a structured measurement tool. This tool was designed to segment the lecture process into minutes and seconds; rows in the table represented time intervals (e.g., 0:10–0:20, 0:20–0:30 ... 39:40–39:50), while columns corresponded to predefined emotion categories. Observers marked the dominant emotion displayed by each student within the respective category for every time interval. Through this systematic coding, time-series-based quantitative frequency data were obtained for each student. A total of three independent observers analyzed the lecture recordings of 40 students and evaluated the emotional processes using this method.

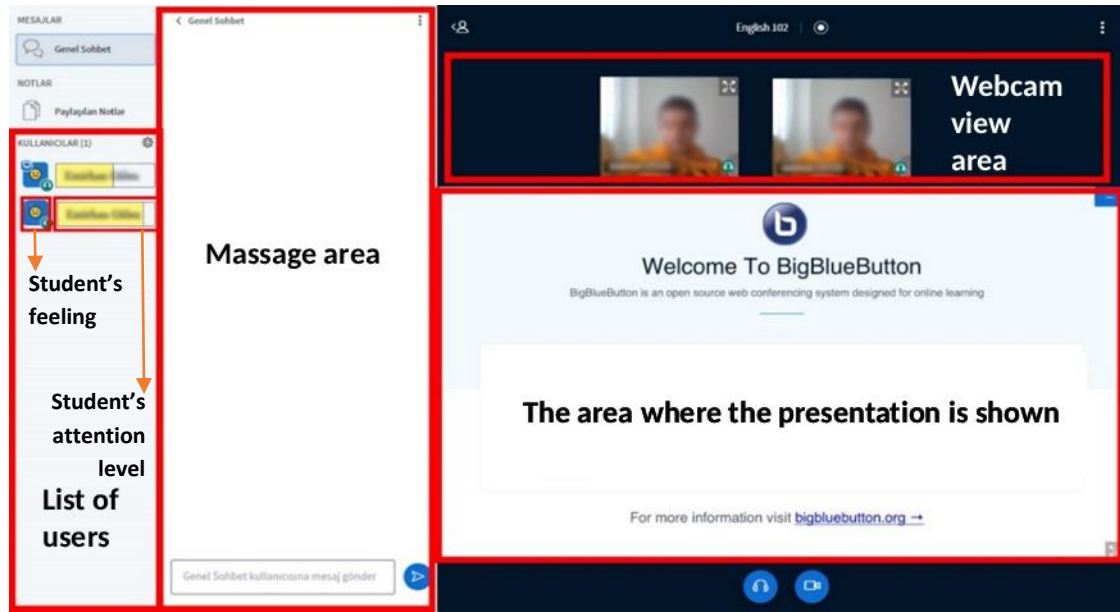
Semi-Structured Interview Form

To identify the factors causing changes in students' emotional and attentional states during the course, semi-structured interviews were conducted. Through these interviews, qualitative data were collected by eliciting students' perspectives. The semi-structured interview form consisted of open-ended questions, which allowed the data to be either expanded upon or delimited as needed (DeJonckheere & Vaughn, 2019). The form was designed to reveal the elements that could influence students' emotions and attention levels. The questions used in the interviews are presented in Appendix 1.

EATS (Emotion and Attention Tracking System)

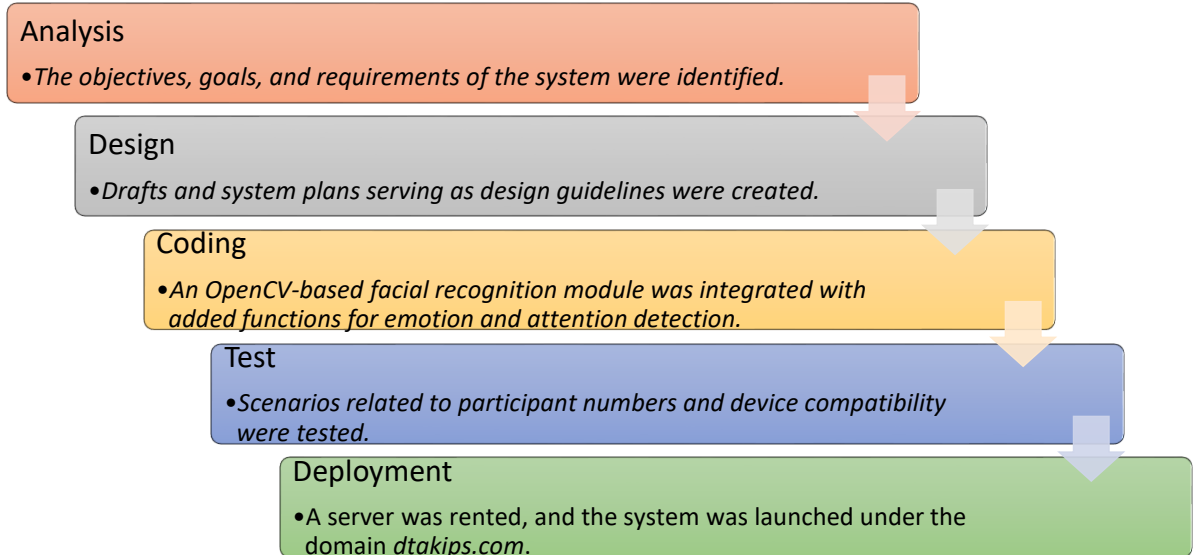
A web-based platform (EATS) was developed within the scope of the study to facilitate live lectures for undergraduate and graduate students. The primary objective of the EATS platform is to identify the different emotions students experience and the levels of attention they demonstrate during live sessions. In detecting emotions through image processing technology, several existing software libraries were utilized. By incorporating these libraries, the study not only leveraged established tools but also explored their further development potential, thereby creating the opportunity to deliver an improved product. An overview of the developed web-based EATS platform is presented in Figure 3.

Figure 1. Introduction of the EATS Platform



As shown in Figure 3, the platform developed on the BigBlueButton live classroom system displays emojis corresponding to users' facial expressions. In this way, the instructor can monitor students' real-time emotions during the lecture. The background colors of the boxes containing students' names change according to their attention percentages, allowing the instructor to easily observe the level of engagement in the class. Access to the emotion and attention data is restricted solely to the instructor. The EATS platform was developed in accordance with the Software Development Life Cycle (SDLC), and the overall process is summarized in Figure 4.

Figure 2. Development Stages of the EATS Platform

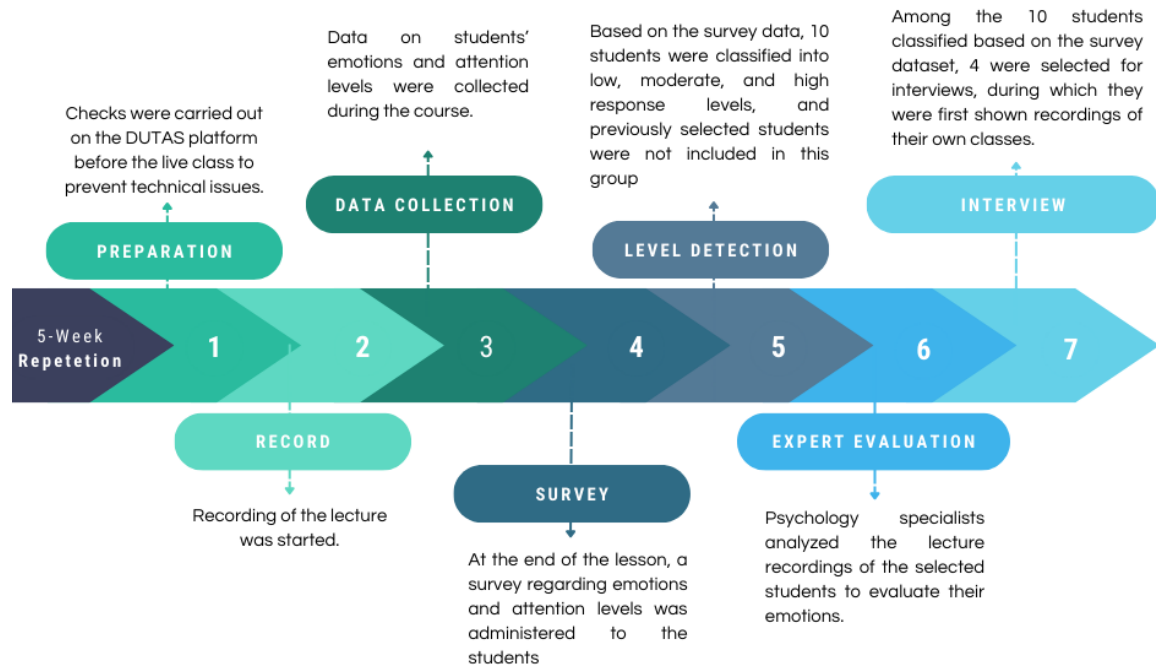


Implementation Process

The study was carried out within the scope of a mixed-methods design and consisted of three main phases over a five-week period (five class hours). The first week was conducted as a pilot implementation, and the data collected during this phase were not included in the study. The implementation process

covered the stages before, during, and after a lecture. An overview of the implementation process is presented in Figure 5.

Figure 3. Implementation Process



As illustrated in Figure 5, the implementation process was repeated consistently over five weeks for a total of five class sessions. At the end of the process, data obtained from the interviews revealed the factors and situations that influenced students, which were subsequently categorized and presented.

Before each lecture, the instructor informed students via the learning management system about access to the live session. Volunteer students were provided with information regarding the minimum technical requirements (e.g., updated browser, microphone, headset). In the pilot session conducted during the first week, students' seamless access to the platform was ensured, and the purpose of the study was explained. Additionally, the functionality of the image processing technology and the questionnaire submission system was tested, and potential technical issues that could arise during the lecture were identified and addressed.

Data Analysis

To address the first research question, the emotion and attention data collected from participants via the EATS platform over four weeks were examined using descriptive analysis. This allowed for the identification of weekly averages of emotions and attention in the classroom, as well as individual variations. Descriptive analysis describes a phenomenon or situation, revealing patterns in the data and addressing the questions of who, what, where, when, and to what extent (Loeb et al., 2017).

For the second research question, descriptive analyses were conducted on both EATS and questionnaire data. In addition, EATS data were compared with observation data using Bland–Altman analysis to examine the agreement between the two measurement approaches. This method stands out because it does not focus on correlation between the two measurements, but rather on the distribution of differences around the mean value, thereby identifying systematic bias and limits of agreement. As such, it provides a more reliable approach than traditional tests when determining whether two measurement methods can be used interchangeably (Giavarina, 2015). The statistical logic of the analysis relies on comparing the mean of the two measurements with their difference on a graph. The mean difference indicates systematic bias, while the ± 1.96 standard deviation values calculated from the

differences define the limits of agreement at a 95% confidence level. The proportion of differences falling within these limits indicates the level of agreement between the methods. In this way, the analysis tested whether there was a relationship between the two sets of measurements and to what extent changes in one influenced the other (Doğan, 2018; Kaur & Stoltzfus, 2017). Bland–Altman analysis was preferred because methods such as correlation or t-tests are insufficient for evaluating accuracy; while correlation only shows co-variation, this method visualizes the acceptability of differences. Thus, it provides clearer judgments regarding the reliability and validity of measurement tools (Franco & Di Napoli, 2017). The analysis was conducted in SPSS 23. Since SPSS does not provide a direct Bland–Altman option, the mean and difference values were first calculated, and then “Scatter/Dot” graph options were used to visualize the data. Lines representing the mean difference and the ± 1.96 standard deviation limits were added, allowing the agreement between EATS and observation data to be assessed both numerically and visually.

To address the third research question, the data obtained from semi-structured interviews were analyzed using content analysis. Content analysis enables data to be systematically interpreted within the framework of themes and meaningful relationships (Yıldırım & Şimşek, 2018). In the first stage of the process, audio recordings were transcribed, and students’ statements were divided into codes and subsequently categorized.

Several measures were taken to ensure the validity and reliability of the data. EATS data were collected directly from system logs, thereby ensuring objectivity, and were gathered regularly under the same conditions for four weeks. In the descriptive analyses, data at the individual level were examined in terms of both means and distributions. In the Bland–Altman analysis, EATS data were compared with the independent evaluations of three expert psychological counselors who reviewed the video recordings. The counselors coded students’ emotional states based on predetermined classification criteria, and in cases of discrepancies, they held brief control meetings to reach a consensus. This process enhanced the reliability of expert observations.

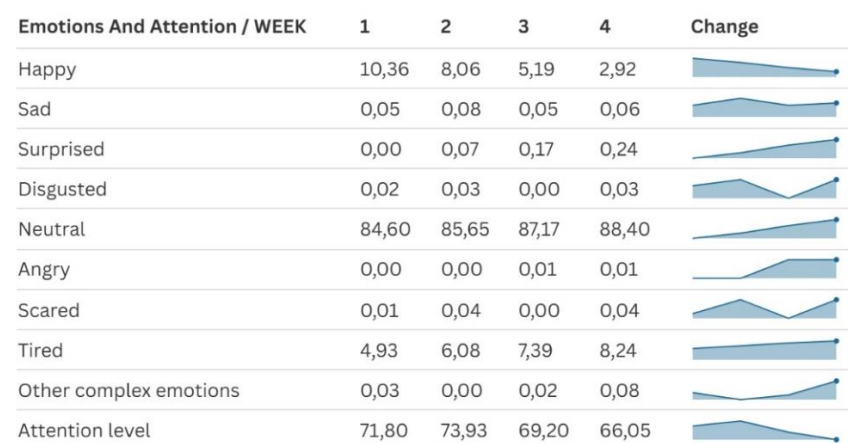
In the qualitative phase, the validity of the semi-structured interviews was increased by preparing the questions in light of a literature review and subjecting them to expert evaluation. The coding process in content analysis was conducted independently by two researchers, and the resulting codes were compared to calculate inter-rater agreement. The high level of agreement strengthened the reliability of the content analysis. Furthermore, students’ statements were supported with direct quotations, thereby enhancing internal validity.

Result

Findings on Weekly Changes in Emotion and Attention Levels

Through four weeks of observations conducted via the EATS platform, quantitative data were obtained regarding students’ emotional states and attention levels during the course sessions. Based on these data, weekly averages were analyzed to examine changes in emotions and attention levels. Figure 6 clearly illustrates the weekly average values and the observed trends.

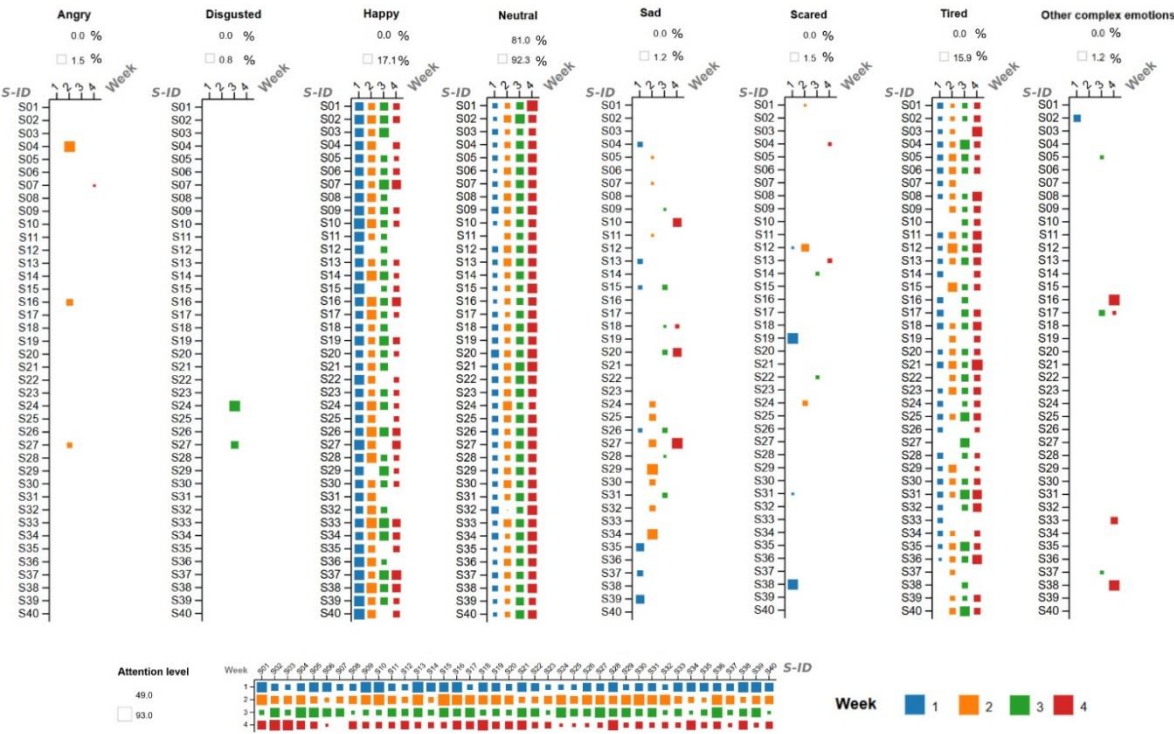
Figure 6. Weekly Change in Students’ Emotions and Attention (% of Total Time)



As shown in Figure 6, the most dominant emotion observed each week was neutral. The proportion of neutral emotion increased from 84.60% in the first week to 88.40% in the fourth week. In contrast, happiness decreased steadily over time, dropping from 10.36% in the first week to 2.92% in the fourth week. This finding suggests a decline in students' motivation or positive emotions toward the course. Meanwhile, fatigue exhibited a consistent upward trend, rising from 4.93% in the first week to 8.24% in the fourth week. This result indicates that the course process may have had an increasingly exhausting effect on students over time.

Figure 7 presents the weekly distribution of individual emotional states and attention levels of the participants (n = 40). Beyond the general averages, this figure allows for the tracking of individual emotional diversity and fluctuations in attention, as well as identifying which students predominantly exhibited less frequent emotions.

Figure 7. Distribution of Students' Emotional States by Week



As illustrated in Figure 7, the neutral emotion remained stable among nearly all participants throughout the weeks. Happiness appeared within a range of 0–17.1%, persisting consistently in some students. Fatigue was widely observed within a range of 0–15.9% and gradually spread to a larger number of participants over time. Other low-frequency emotions (e.g., fear, sadness, disgust, anger) were expressed by fewer students but emerged in certain weeks, reflecting the diversity of emotional states. Attention levels showed meaningful individual differences, with fluctuations observed on a weekly basis.

Overall, students predominantly remained in a neutral emotional state during the learning process, while a decline in happiness and an increase in fatigue were recorded. Attention levels were relatively high in the initial weeks but displayed a fluctuating trend as the process progressed. These findings suggest that students' emotional and cognitive processes changed over time, and that increases or decreases in specific emotions reflected the dynamic and evolving nature of their learning experiences.

Findings on the Agreement Between Measurement Methods

This section presents the significance levels of emotions and attention in the analysis of data obtained through different methods. To answer the related research question, participant questionnaire

data were analyzed, and four-week averages and standard deviations for each emotional state and attention level were calculated. To interpret the means, specific ranges were determined; by applying the formula $(5-1)/5$, intervals of 0.8 were established:

- Items between 1.0 and 1.8 indicated that the data measured by EATS were perceived as very little accurate.
- Items between 1.8 and 2.6 indicated that the data measured by EATS were perceived as slightly accurate.
- Items between 2.6 and 3.4 indicated that the data measured by EATS were perceived as moderately accurate.
- Items between 3.4 and 4.2 indicated that the data measured by EATS were perceived as highly accurate.
- Items between 4.2 and 5.0 indicated that the data measured by EATS were perceived as very highly accurate.

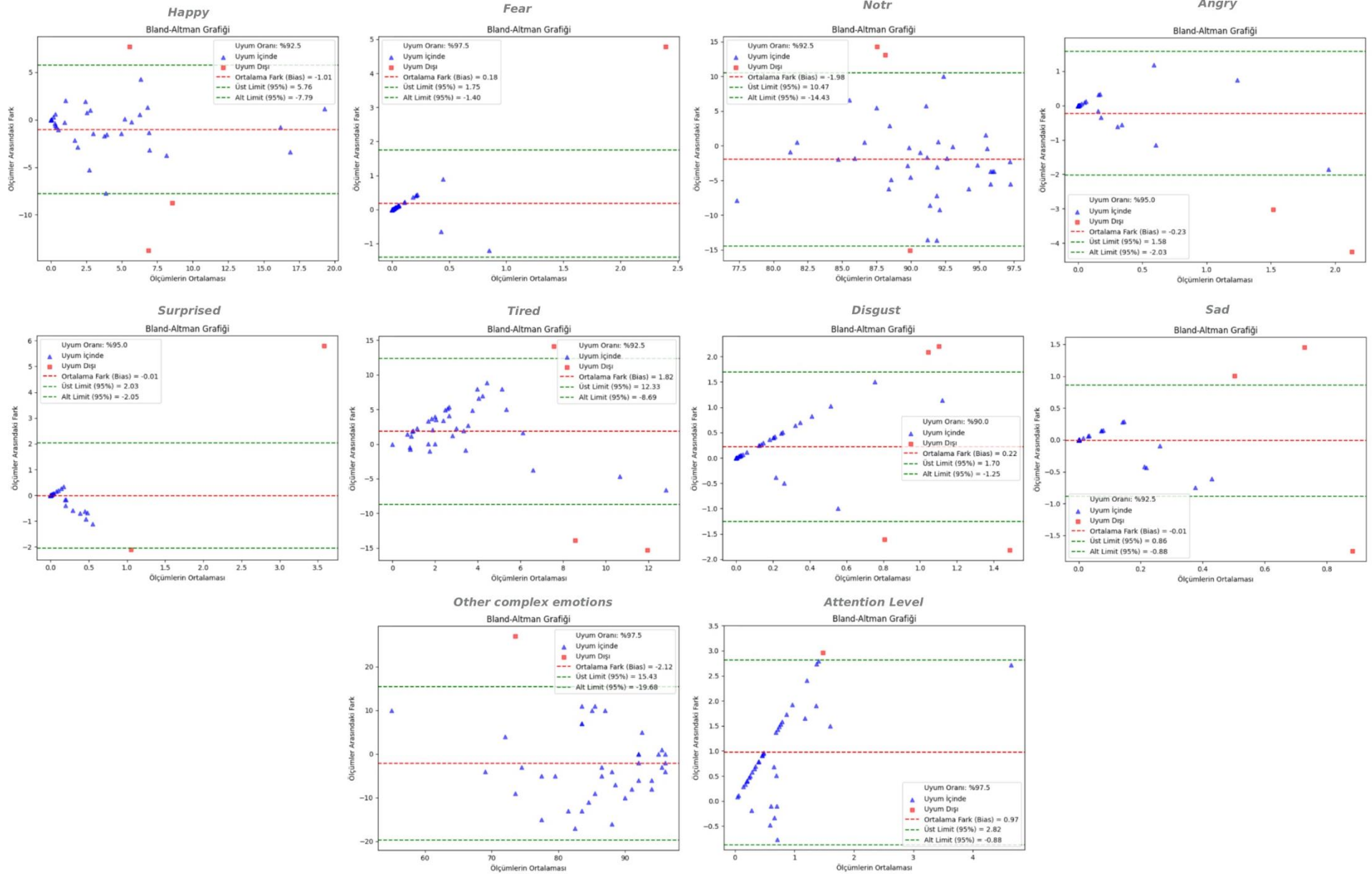
Over the course of four weeks, a total of 40 participants completed one questionnaire per week, resulting in 160 questionnaire responses. The analysis of the obtained data regarding attention levels and emotional categories is presented in Table 2.

Table 21. Survey Results

Survey Items	N	f	Range	$\bar{X}$	SS
Happy	40	160	High	3.48	3.46
Scared	40	160	Partially	3.33	0.80
Neutral	40	160	High	4.19	6.36
Angry	40	160	High	3.55	0.92
Surprised	40	160	High	3.49	1.04
Tired	40	160	High	3.41	5.36
Disgusted	40	160	Partially	3.09	0.75
Sad	40	160	High	3.47	0.44
Other Complex Emotions	40	160	High	3.71	0.94
Attention Level	40	160	High	3.90	8.96

To evaluate the agreement between the data collected through EATS and the observation method, separate Bland–Altman analyses were conducted for attention levels and each emotion. The findings regarding attention and emotions are presented in Figure 8.

Figure 8. Bland–Altman agreement plots for attention level and emotions obtained via EATS and observation method



According to the Bland–Altman analysis, the differences between measurements for happiness, surprise, sadness, and fear were found to be quite small, with agreement rates ranging between 92.5% and 97.5%. This indicates a high level of consistency between EATS and the observation method. Although the mean differences for the variables of neutral and fatigue were higher compared to other emotions, the distributions remained within acceptable limits, demonstrating significant parallelism between the methods. For anger, disgust, and complex emotions, agreement rates were approximately 90%. While some outliers caused deviations, the overall consistency remained reliable.

For attention levels, a strong overlap between the two methods was observed, with agreement calculated at 97.5%. Overall, the vast majority of measurements across all variables fell within acceptable limits, indicating that EATS demonstrates a high level of agreement with the observation method. Table 3 presents the agreement levels between EATS and expert observations (based on Bland–Altman analysis) for emotions and attention, alongside the average levels reported by participants through the questionnaire. While the agreement values illustrate the degree of systematic bias and boundaries between the two measurement methods, the questionnaire averages reflect students' subjective evaluations. Thus, the table enables a holistic assessment of both the consistency of measurement methods and participants' perceptions of the system's accuracy.

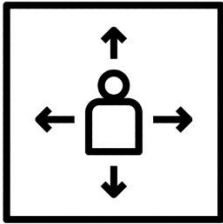
Table 3. EATS, Gözlem Yöntemi ve Anket Verilerinin Karşılaştırılması

Emotions / Attention Level	EATS & OBSERVATION (Agreement Values)	Survey	Verbal Equivalent of Survey Value
Surprised	95	3.49	High
Sad	92.5	3.47	High
Attention Level	97.5	3.90	High
Angry	90.0	3.55	High
Afraid	97.5	3.33	Partially
Happy	92.5	3.48	High
Disgusted	90	3.09	Partially
Neutral	92.5	4.19	High
Tired	92.5	3.41	High
Other Complex Emotions	97.5	3.71	High
Average	93.75	3.56	High

Findings on the Factors Influencing Students' Emotions and Attention in Live Lectures

To identify the factors influencing students' emotions and attention levels during live lectures, semi-structured interviews were conducted with 16 students. The interview data were analyzed, and categories and codes were generated based on students' perspectives regarding the factors affecting their emotional and attentional states. A summary of the analysis findings and their frequencies is presented in Figure 8.

Figure 8. *Students' Opinions on Factors Affecting Their Emotions and Attention in Online Course*

	LECTURER	TECHNICAL ISSUES	PHYSICAL ENVIRONMENT	LEARNING MATERIAL	STUDENT	PEER
THEME						
CODE	+ Changing tone of voice f(10) + Utilizing the question and answer method f(7) -- Deficiency in technical knowledge f(4) + Methods used while conducting the lesson f(4) + Friendly behaviors f(4) + Joining with camera on f(3)	-- Interruption of student's internet connection f(12) -- Loss of the instructor's internet connection f(4)	-- Factors in the student's live lesson environment f(9)	+ Inclusion of visual elements in lesson presentations f(6)	+ Situations that enhance student readiness f(5)	+ Peers' positive verbal and, if possible, video participation f(2)
EVIDENCE FOR THE CODE	"The instructor's tone changes have a positive effect on me" (Student 6, Female) "Asking questions during the lesson boosts our attention and keeps us engaged." (Student 11, Male)	"Both the instructor and we can experience internet disconnections" (Student 6, Female)	"A quiet and calm environment greatly affects me" (Student 14, Male)	"I strongly dislike text-heavy presentations without visuals." (Student 12, Male)	"I perform better in class when I'm prepared and familiar with the topic." (Student 12, Female)	"Active participation of my classmates increases my motivation." (Student 12, Male)

+ Positive Direction of Effect
 -- Negative Direction of Effect
 f (Number) Frequency Count

As illustrated in Figure 8, students were found to be influenced during live online classes by factors such as the instructor, technical problems, physical conditions, learning materials, and peers. Students reported that instructors' reliance on a single tone of voice negatively affected their emotions and attention levels: "If the instructor keeps explaining only one topic in the same tone of voice, after a while my focus inevitably drifts." (Student 11). It was also observed that when students took on more active roles, their emotions and attention levels were positively influenced: "For example, when the instructor asks a question in the middle of the class, it really grabs our attention. It makes you listen more closely." (Student 8). The instructional methods and techniques adopted by instructors were highlighted as an important factor affecting students' attention levels: "Of course, the method the instructor uses also matters. Like, is it cooperative learning, or is the teacher just lecturing? Does the teacher first explain and then let us practice, or ask us questions and wait for answers? These things really affect our attention." (Student 16). Students emphasized that when instructors demonstrated the ability to solve technical problems efficiently, it fostered a sense of trust and strengthened their emotional and attentional connection to the lesson. Conversely, delays created distractions: "When the instructor can quickly solve technical problems during class, it gives us confidence and strengthens our focus and connection to the lesson. But if it takes too long—for example, when the teacher has to upload or share a document—it eats into our time and makes us lose focus." (Student 13).

The instructor's sincerity during live lectures was also reported to increase positive emotions and support students' attention: "The teacher's sincerity makes a big difference. Because our instructor was warm and sincere, we didn't lose focus during the live classes. That kind of sincerity is a huge plus—it increases happiness and reduces anxiety. I'd say it's one of the most important things." (Student 2). Other factors noted by students included the instructor's camera use, body posture, and angle, which influenced both emotions and attention: "The instructor's camera use also affects me. If the camera is off, I get distracted more easily. But if the teacher turns it on, I can focus better and understand the lesson more clearly." (Student 13). Peer participation was also identified as a determinant of emotional engagement, as it fostered a sense of belonging and encouraged active involvement: "Class participation is important. If students don't participate, the instructor becomes tense, and that tension spreads to the whole environment. It creates a stressful atmosphere, like 'why aren't you participating?'" (Student 5).

Technical problems emerged as another significant factor influencing students' emotions and attention: "Internet connection problems happen both on our side and on the teacher's side." (Student 6). Students expressed a preference for more visual learning materials, noting that visuals enhanced focus and engagement: "Some instructors prepare slides full of text from beginning to end, and that makes it really hard to concentrate. It's boring. But if they explain with images and comparisons, it feels more fun, and we can focus better thanks to visual memory." (Student 6). Furthermore, certain teaching strategies, such as reviewing prior lessons, were found to help direct students' attention: "Our instructor used to start the first 15 minutes by reviewing the previous lesson. While going over it, they would ask us questions, and that really helped direct our attention to the class." (Student 3).

Discussion

Are There Significant Weekly Changes in Emotion and Attention Levels?

This study revealed that students experienced notable changes in both their emotional states and attention levels over the course of four weeks. Overall, the findings showed that neutral emotion was dominant; levels of happiness declined in subsequent weeks, while fatigue exhibited a partial increase. Meanwhile, attention levels were relatively high in the initial weeks but followed a fluctuating pattern in later weeks. Other emotions were expressed at very low frequencies by students.

The dominance of neutral emotions, ranging between 84% and 88%, indicates that students maintained emotional stability during the learning process, which can be considered an expected outcome for lecture-based settings (Gasper et al., 2021). The decline in happiness suggests that students

may have experienced monotony or loss of motivation during the course, whereas the increase in fatigue could be related to screen time, lesson pace, and cognitive load (Bakır-Yalçın & Usluel, 2023). Zembylas (2008) emphasized that online learners' emotions tend to evolve into anxiety and frustration over time, while Shin and Chan (2004) highlighted that increasing feelings of loneliness and stress can negatively affect students' engagement and performance. These findings suggest that online learning should be approached not only from a cognitive perspective but also from an emotional one, as motivation, engagement, and achievement are closely tied to emotional resilience and support (Pekrun, 2014).

The observation of low-frequency emotions in certain students over limited weeks demonstrates that learning experiences vary according to individual differences. Fluctuations in attention and the emergence of negative emotions may limit active participation and adversely affect academic performance. Therefore, providing emotional support to learners is recommended (Shin & Chan, 2004; Zhu et al., 2022; Kong et al., 2024). This highlights the need for online learning processes to be carefully designed not only academically but also with attention to emotional and cognitive dimensions.

Agreement Between EATS and Observer Forms in the Live Lecture Environment

In this study, the EATS platform was evaluated as a system designed to measure students' emotions and attention levels through facial expressions. Bland–Altman analyses and participant surveys revealed that the platform provided high accuracy in detecting basic emotions and attention. For emotions such as neutral, happy, sad, fearful, surprised, angry, and disgusted, as well as for attention, agreement levels exceeded 90%, with consistency above 95% particularly for neutral emotion and attention. Moreover, EATS measurements enabled real-time assessment by monitoring the temporal changes in students' emotional and cognitive states throughout the four-week course period (Fidan & Usluel, 2023).

In the literature, studies on the use of emotion recognition systems in online learning remain limited (Bahreini et al., 2016a; Conflitti et al., 2009). For instance, voice-based systems have been reported to achieve only about 30% accuracy (Conflitti et al., 2009), whereas facial expression–based systems reach 72%, and multimodal approaches increase accuracy to 96–98.6% (Bahreini et al., 2015; 2016b). This highlights the limitations of single data sources and the advantages of multimodality in terms of reliability. However, wearable or head-mounted devices are not preferable, as they may negatively affect students' learning experiences (Lin et al., 2014).

EATS demonstrated reduced accuracy in detecting fatigue and complex emotions. This is consistent with the broader literature, which notes that most systems focus primarily on basic emotions and experience performance declines when classifying complex affective states (D'Mello & Calvo, 2013). Environmental and individual factors also constitute limitations: students concealing their faces, sitting in poorly lit environments, or deliberately suppressing their emotions may affect system accuracy (Zhou et al., 2024; Kim & Ketenci, 2020; Lyu et al., 2022). Approaches such as multi-frame analysis and transfer learning models have been shown to produce more reliable results compared to single-frame analysis (Pordoy et al., 2024).

In conclusion, while EATS provides reliable results for basic emotions and attention levels, complex emotions and individual or environmental factors remain significant limitations. In line with recommendations from the literature, multimodal and context-aware systems offer greater potential for more accurate and comprehensive analyses of emotional processes (Cernea & Kerren, 2015).

Factors Influencing Students' Emotions and Attention in Live Lectures

The instructor is the most critical actor in planning and managing the educational process. Students' levels of attention and emotional states are largely shaped by the instructor's pedagogical, technical, and communicative competencies. As the central figure in students' live lecture experiences, the qualifications of instructors must be carefully evaluated. In particular, pedagogical competencies are essential for planning and delivering lessons that meet students' needs, while technical competencies

1 ensure the effective use of the online environment. Together, these elements facilitate the development
2 of positive emotions and the maintenance of attention during the learning process. Indeed, studies have
3 shown that as instructors' pedagogical skills improve, students' positive attitudes toward the course also
4 increase (Berge, 2008). Similarly, instructors' ability to effectively utilize technical infrastructure and
5 digital tools plays a crucial role in the continuity and effectiveness of live lectures. In this regard, Varvel
6 (2007) emphasized the importance of instructors acquiring the technical competencies required to adapt
7 to online teaching environments. Moreover, examples provided by instructors to enhance clarity in
8 lectures have been shown to help students maintain focus and foster positive emotions (Heilporn et al.,
9 2021).

12 Another important dimension is instructors' communication skills. The effective use of tone of
13 voice, gestures, and facial expressions during lectures increases student interest and contributes to
14 greater attention and emotional engagement in the learning environment. In particular, Brooks and Young
15 (2015) found that instructors' verbal immediacy and sense of presence in online settings were closely
16 associated with students' development of positive emotions toward the course. These findings are
17 especially meaningful in the context of live online lectures that became widespread during the COVID-19
18 pandemic.

21 A further factor influencing the effectiveness of live lectures is peer interaction. Active participation
22 by peers during lessons helps transform the classroom from a purely teacher-centered model into a more
23 interactive environment. Research conducted by Bober and Dennen (2001), Muilenburg and Berge (2001),
24 Bezuidenhout (2009), and Cao et al. (2009) has indicated that interaction with both instructors and peers
25 has positive effects on participation, satisfaction, and overall learning experiences. Such interaction
26 increases the dialogue between the student and the learning environment, as emphasized by Moore
27 (1973), thereby reducing the perception of "distance" and reinforcing a sense of belonging to the class.
28 These forms of engagement have been found to trigger positive emotions among students and enhance
29 their commitment to live lectures (Tu et al., 2025).

32 On the other hand, technical problems are among the major negative factors that directly affect
33 students' attention levels in online environments. In particular, internet connection issues disrupt
34 students' engagement with the lesson and reduce their span of attention. Studies by Bayrak (2020) and
35 Chou and Liu (2005) showed that such problems decrease student satisfaction and negatively influence
36 participation. More recently, Liu and Xie (2024) reported that connection failures, audio interruptions,
37 and screen-sharing difficulties trigger emotions such as boredom and frustration, leading to higher levels
38 of distraction during online lectures.

41 The quality of instructional materials is another determinant of students' attention and emotional
42 states. Students indicated that text-heavy presentations were not engaging, whereas lessons enriched
43 with visual content, graphics, and summarizing infographics enhanced their motivation. While lectures
44 relying solely on verbal explanation often resulted in attention loss, visually supported presentations were
45 observed to extend students' attention spans (Lange & Costley, 2020).

48 Students' prior knowledge of course topics also has a direct impact on their attention and emotions
49 during live lectures. Learners with sufficient background knowledge were able to participate more
50 comfortably in the learning process, which, in turn, increased both positive emotions and attention levels.
51 Winter et al. (2013) found significant differences in participation levels depending on students' prior
52 knowledge. Similarly, Chien et al. (2022) reported that students' levels of boredom in online classes were
53 directly related to the difficulty of the content and the adequacy of their prior knowledge.

56 Alongside these factors, students' physical learning environments also emerge as an important
57 variable. Noise, crowded spaces, non-ergonomic seating, and inadequate lighting disrupt attention and
58 reduce motivation. Researchers such as Bayındır (2022), Uzelac et al. (2015), and Elcil and Şahiner (2014)
59 have emphasized the role of environmental conditions in influencing students' attention during lessons.

Hollister et al. (2022) further highlighted that students' physical surroundings during live online lectures significantly impact both their emotional responses and attention spans.

Taken together, these findings suggest that students' attention and emotions in online learning environments are shaped by a multilayered structure. Factors ranging from instructors' pedagogical skills to technical infrastructure, from content design to social interaction, and from students' prior knowledge to their physical environment jointly influence the process. Therefore, the effective design of live online learning environments requires a holistic approach, taking into account the impact of each dimension on learners, and implementing targeted improvements accordingly.

Conclusion

This study demonstrates that students experienced significant changes in their emotional and attentional states over four weeks of online lectures. The findings indicate that students predominantly remained in a neutral emotional state, while happiness levels gradually decreased and fatigue increased. Attention was relatively high at the beginning of the process but followed a fluctuating trend in subsequent weeks. These results highlight the need to address not only the cognitive but also the emotional dimensions of online learning.

The evaluations conducted through the EATS platform and external observers showed high levels of agreement, with over 90% accuracy for basic emotions and attention. However, the accuracy of detecting complex emotions was lower, underscoring the need for multimodal solutions.

The study further revealed that the most critical factor in students' live lecture experiences is the instructor's pedagogical, technical, and communicative competencies. The effective use of examples, visual materials, gestures, facial expressions, and tone of voice by instructors enhanced students' attention and motivation, while interactive lecture structures reduced the sense of "distance" and strengthened learners' sense of belonging.

Recommendations

- Course design and content: While plain lecturing often leads to attention loss, lessons enriched with visuals, graphics, and infographics increase students' interest and motivation. Instruction should avoid monotony and incorporate diverse materials.
- Pedagogical and communication skills: Instructors should provide clear examples, use tone of voice and body language effectively, and foster student interaction. Such practices contribute to positive emotions and sustained attention.
- Technical infrastructure: Reliable internet connectivity and appropriate software support are essential for uninterrupted live sessions. Connection problems trigger boredom and distraction among students.
- Social interaction: Peer engagement and group work enhance dialogue with the learning environment, reduce the sense of "distance," and strengthen commitment to the course.
- Emotional support: Guidance and counseling mechanisms should be integrated to help students cope with negative emotions such as loneliness, stress, and fatigue.
- AI-based personalization: The analysis of emotional and attentional data through artificial intelligence algorithms can enable personalized content, feedback, and interaction strategies, thereby increasing student engagement and motivation.

Limitations

This study has several limitations. Although the EATS platform demonstrated high accuracy in measuring basic emotions, it was limited in detecting complex emotions. Environmental factors—such as lighting conditions, camera use, and students concealing their faces—as well as students' deliberate suppression of emotions affected the validity of the measurements. Moreover, the four-week observation period and the implementation of the study within a single institution restrict the generalizability of the

findings. To achieve more accurate detection of complex emotions, future research should integrate multimodal systems that combine facial, vocal, and behavioral data.

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27 **Appendix-1. SEMI-STRUCTURED INTERVIEW QUESTIONS**

28 **Factors Affecting Emotion and Attention**

29 What is the reason for your high or low level of emotions (e.g., happy, angry, surprised – whichever is
30 predominant for each individual) during the relevant class? What affects these emotions?
31 During the live lesson, what factors have influenced your attention and emotional state (positively or
32 negatively)?
33
34

- 35 1.1. In terms of your personal life and problems,
36 1.2. In terms of the physical environment you are connected to the live lessons (temperature, humidity,
37 light, sound, tools/equipment/other people in the environment/technological devices),
38 1.3. In terms of the intensity of the lesson and the topic,
39 1.4. In terms of whether the interface of the platform used for the live lesson is good or bad,
40 1.5. In terms of the teacher's attitudes and behaviors,
41 1.6. In terms of the lesson material/content/topic/duration:
42 1.6.1. How do your emotions and attention toward the lesson change depending on the lesson topic and
43 content?
44 1.6.2. How do your emotions and attention toward the lesson change depending on the learning-
45 supporting materials used in the lesson?
46 1.6.3. How do your emotions and attention toward the lesson change depending on the duration of the
47 live lessons?
48 1.7. In terms of interaction with peers, such as chatting, asking and answering questions, and increasing
49 engagement,
50 1.8. In terms of technical issues (originating from you/teacher/system, computer, internet speed, etc.)
51
52
53
54

55 In which of these items are your emotions more affected, and in which are your
56 attention levels more affected?

57 Besides the issues discussed above, are there any other situations that affect your
58 emotions and attention toward live lessons?
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Appendix-2. IMAGES FROM ONLINE COURSE SESSIONS

