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Analysis of Emotional and Attentional Changes in Students During Online Education: The Case of Tourism Education

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Abstract

Purpose – This study aims to analyze the impact of changes in the emotional states and attention levels of academics and students during online education on the learning process.

Methodology – Emotional data analysis and attention measurements based on facial expressions were employed. Analyses were conducted for both students and the academic instructor over four consecutive weeks within a 14-week course at Balıkesir University Faculty of Tourism.

Findings – The analyses revealed statistically significant week-to-week differences in students' attention and emotional indicators. Attention levels increased after the first week, peaked in Week 3, and slightly declined in Week 4. In contrast, arousal and positivity levels demonstrated a gradual downward trend over time. Emotional valence fluctuated across weeks rather than following a linear trajectory. Neutral and sadness emotions were frequently observed throughout the study period. The instructor's emotional tone shifted from relatively higher negative expressions in the early weeks toward a more neutral and balanced state in later weeks. The instructor's emotional tone shifted toward a more neutral state in later weeks.

Conclusions – These findings indicate that emotional and attentional responses in online learning environments are dynamic and non-linear. Rather than reflecting continuous improvement, emotional engagement evolves through fluctuating patterns across time. The results emphasize the importance of integrating emotional and attentional considerations into the evaluation and design of educational processes to foster more responsive and effective learning environments.

INTRODUCTION

Online education has become an increasingly widespread method of learning, driven by rapid advancements in educational technologies. The expansion of web-based education and internet technology has given rise to virtual courses, libraries, and universities, which eliminate geographical constraints. Compared to traditional models, these approaches implement more practical and modern methods to deliver effective and efficient education. Officially beginning in the 1930s (Odabaş, 2003), distance education has gained significant popularity, particularly following the COVID-19 pandemic (Ünal & Bulunuz, 2020). Today, online education is heralded as the future of learning (Lee & Jhung, 2019).

However, evaluating the effectiveness of these learning environments requires a thorough examination of the emotional and cognitive factors influencing the learning process. Alongside the cognitive dimensions of learning, it is well-established that emotional states and attention processes play a crucial role in shaping educational outcomes (Pekrun et al., 2002). Emotions are fundamental components that direct students' attention, enhance their motivation, and support their information processing (Sommer et al., 2008).

In the context of online education, monitoring students' emotional responses and attention levels offers significant potential for individualizing and improving educational processes. Artificial intelligence-based facial expression and attention tracking systems have emerged as innovative tools to measure students' emotional states and attention levels. Detecting emotions in online learning is more challenging compared to face-to-face settings due to the lack of emotional cues (Kımav, 2023).

To address this, various methods have been developed to analyze students' emotional and attentional states. Among these, "MorphCast Emotion AI" and the "Generative Pre-trained Transformer-4" language model are the most notable (Robert, 2024; Hellgren & Sokolov, 2023). These models analyze facial expressions, gestures, and attention responses, providing supportive data for enhancing educational processes.

This is particularly significant in dynamic, highly interactive fields like tourism education, where understanding students' emotional needs and increasing their engagement in the learning process is vital. This study investigates the analysis of emotional and attentional changes based on facial expressions in an online education setting and examines how these changes influence learning processes.

1. THEORETICAL BACKGROUND

1.1. The Importance of Emotion in Learning

Learning is a process that integrates concepts such as attention, motivation, and emotion, enabling the mental processing of information (Liv et al., 2020; Arseven, 2023). Theories explaining the learning process include behavioral theories, social learning theories, brain-based learning theories, and cognitive learning theories. Except for behavioral theories, most converge on the significance of two core concepts: attention and emotion. Attention plays a critical role in initiating and enhancing the learning process. Motivation, a key determinant of attention, directs it toward defined goals and objectives and is closely related to memory and decision-making (Pekrun et al., 2002).

Emotions, defined as periodic and synchronous changes producing adaptive and physiological responses that help interpret stimuli more efficiently (Arseven, 2023), are another pivotal factor that triggers learning and influences both the learning process and success (Sommer et al., 2008; Pekrun et al., 2014; Tyng et al., 2017). Emotions guide both attention and motivation during learning while also affecting memory processes. Consequently, attention and emotions significantly contribute to students' learning activities and academic success (Bechara et al., 2005). Simply put, emotions play a crucial role in fostering cognitive processes, capturing students' attention, and enhancing their motivation (Liv et al., 2020).

Despite this, an overemphasis on academic skills and achievements often sidelines the role of social-emotional intelligence in the learning process (Bozgün & Akın-Kösterelioğlu, 2021). As a result, students' overall learning experiences remain incompletely understood. Intellectual capability alone does not

guarantee success; a learning process overly focused on intellectual abilities can hinder students' awareness and management of their emotions (Gümüş, 2022).

The impact of emotional states on learning is closely tied to individuals' understanding of their own and others' emotions (Erdem et al., 2013). Emotions also play a key role in helping individuals adapt to their social environment. For emotions to positively influence the learning process, students must understand both their own and others' emotions, developing into emotionally sensitive individuals. Studies on the impact of social-emotional states on learning reveal that emotional intelligence contributes to academic success, lifelong learning, effective communication with diverse individuals, and resolving social-emotional challenges (Cohen et al., 2005).

Based on these findings, it is essential to provide environments that foster students' social-emotional intelligence skills (Buchanan et al., 2009). Consequently, social learning programs have been developed to support and guide students in both school and extracurricular settings.

The concept of emotional intelligence, introduced in the 1990s, encompasses abilities such as self-motivation, the development of social skills, understanding others' emotions, and self-awareness (Yeşilyaprak, 2001). Although emotional intelligence was initially widely embraced, its significance has diminished over time, giving way to the dominance of academic intelligence. However, emotional intelligence remains essential for societal development. In this context, all stakeholders in the education process must adopt attitudes and behaviors that promote emotional intelligence (Kocayörük, 2004).

1.2. Attention and Methods of Measuring Attention

The concept of attention, extensively studied across various disciplines, holds critical importance in learning, performance, health, daily life, and more (Bruya & Tang, 2021). Attention is defined as the focus of consciousness on a particular point. However, attention often encounters multiple stimuli simultaneously (Keller et al., 2020). For example, while reading this article, your attention might shift to other materials. Due to the limited capacity of the nervous system and specific objectives, the organism must act selectively. Under the right conditions, it is expected that individuals will focus on the intended material. Regardless of how well a lesson is designed, a distracted student will miss the content and lose interest in the lesson (Glotzbach, 2024).

To prevent this, various studies have been conducted and continue to be conducted in the field of education. Research often addresses factors such as silence in schools, instructional speaking durations, group work, individual interaction, learning performance, mindfulness, lack of motivation, lack of materials, difficulty understanding materials, and hyperactivity as ways to improve students' attention levels (Suarez & Eduardo, 2023).

Attention-related conditions, such as attention deficit hyperactivity disorder (ADHD), recognized by both physicians and society, are increasingly prevalent in education (Öner, Öner & Aysev, 2003). ADHD, characterized by an inability to focus due to neurophysiological differences in the brain, requires in-depth studies for diagnosis and solutions (Arseven, 2023).

1.2.1. Strategies for Enhancing and Measuring Attention

Effective use of teaching and learning strategies is essential to address attention-related challenges. Learning strategies foster interaction, facilitate learning, and enhance retention. These strategies include:

- Attention strategies
- Strategies to enhance short-term memory storage
- Strategies to strengthen meaning-making (encoding)
- Strategies to enhance retrieval (recall)
- Motivation strategies
- Executive cognitive strategies (Senemoğlu, 2012).

Determining the extent and manner of students' attention to classroom topics can be challenging, as various types of attention lapses occur during lessons. These lapses can be categorized as internal or external attention. Therefore, when addressing attention, teachers must focus not only on learning strategies but also on instructional strategies. For meaningful learning, teachers should employ diverse teaching approaches, methods, and techniques (Çoban et al., 2021).

1.2.2. Instructional Techniques

According to Saskatchewan Education (1991), instructional techniques can be classified as follows:

- *Direct instruction*: Lecturing, asking didactic questions, practice exercises, demonstrations, providing examples, and explanations.
- *Indirect instruction*: Reflective discussions, concept mapping, problem-solving, guided inquiry.
- *Experiential instruction*: Simulations, surveys, field observations, experiments, games, role-playing, drama.
- *Interactive instruction*: Group or class discussions, collaborative learning, brainstorming, laboratory work, problem-solving.
- *Independent instruction*: Homework, research projects, reports, essays, and constructed questions.

All classifications include actions related to attention, underscoring its significance. Supporting this, Gagné (1985) emphasized that "attention" should be the primary action in any effective teaching model.

1.2.3. Types of Attention in Classroom Contexts

In classroom settings, attention can be categorized as **internal vs. external attention** and **topic-related vs. off-topic attention**. Chun et al. (2011) developed a taxonomy to explain and classify attention states in classrooms simply. These classifications involve a focus on external/internal attention and topic-related/off-topic dimensions. For example:

- *Topic-related external attention*: A student focusing on lecture slides and listening to the instructor.
- *Topic-related internal attention*: A student recalling a previously learned theory during a discussion and linking it to new information.
- *Off-topic external attention*: A student watching movements outside the window or listening to classmates' whispers during the lesson.
- *Off-topic internal attention*: A student recalling unrelated events or situations during the lecture (e.g., a family member's hospitalization or purchasing a new car).

Attention plays a pivotal role in ensuring effective learning. By understanding different attention states and integrating targeted instructional strategies, educators can foster a more engaging and focused learning environment.

1.3. Technology-Assisted Emotion and Attention Analysis (AI-Based Facial Expression and Attention Tracking Systems)

The rapid advancement of technology in recent years has underscored that the only constant is change itself. Consequently, the role of technology in education has gained critical importance, sparking discussions on how to integrate it effectively for maximum efficiency (Oktay & Çakır, 2013). Traditional face-to-face learning environments are now being enriched by smart classroom systems and multimedia educational technologies, offering diverse emotional experiences that enhance student engagement in lessons. Numerous applications have been developed in this context. For instance, the Turkish Ministry of National Education has continuously invested in technology, integrating modern advancements into the educational system.

When using technology-supported instructional materials, it is crucial to carefully consider their emotional impact on students. Attention, which is influenced by emotions, plays a key role in learning, memory, and problem-solving (Seli et al., 2016). Thus, behavioral inference based on facial expressions, gestures, and speech is used to identify emotions accurately. Emotional analysis, which initially emerged in engineering, is now widely applied in education and workplace behavior analysis (Yurdasever, 2024). It aims to identify and classify individuals' emotional states (Zucco et al., 2017) and can be described as “the extraction of emotions from unstructured sources such as text, images, or audio” (Chaudhury et al., 2022: 611). Among the various terms for this field, "emotion analysis" remains the most frequently used (Liu, 2012).

1.3.1. Emotion Analysis in Online Learning

When considering the relationship between technology and education, online learning emerges as a prominent concept. The number of learners utilizing online resources has grown rapidly due to the flexibility they offer, enabling learning anywhere and anytime (Batra et al., 2022). However, understanding students' emotions, perceptions of lessons, or attention levels in online learning environments has

become a critical question. Analyzing students' responses during classroom and online sessions is essential to assess their engagement and success in the learning process (Kim & Yoon, 2018).

The emotional states elicited by external and internal stimuli in learners are as important as their attentional states, which serve as focal points among their internal thoughts (Gülen & Göktaş, 2023). To examine students' emotional and attentional states, various methods have been developed, including Electroencephalography (EEG), Functional Magnetic Resonance Imaging (fMRI), Functional Near-Infrared Spectroscopy (fNIRS), Galvanic Skin Response (GSR), Eye Tracking, and Heart Rate measurements. Neuroimaging techniques are among the most frequently used methods in this field (İde & Gündüz, 2024).

Computer-based approaches focus on facial expressions using tools such as OpenFace, Histogram of Oriented Gradient (HOG) (Madhuri & Negi, 2023), Support Vector Machine (SVM) (Wang et al., 2010), Scale Invariant Feature Transform (SIFT) (Nixon & Aguado, 2012), Speeded Up Robust Features (SURF) (Bay et al., 2008), DenseNet-121 (Li, 2022), ResNet-18 (Batra et al., 2022), and MobileNetV1 (Yulita et al., 2023). Additionally, datasets and tools such as DAiSEE (Gupta et al., 2016), FER2013 (Diaz et al., 2024), MotiSpectra (Brast et al., 2024), and systems like MorphCast Emotion AI (Guerrero et al., 2023) and the GPT-4 language model have been applied to emotion analysis. Among these, MorphCast Emotion AI (Hellgren & Sokolov, 2023) and Generative Pre-trained Transformer-4 (Robert, 2024) are the most well-known.

1.3.2. Facial Expression Analysis in Online Learning

These methods analyze students' facial expressions during online learning sessions to interpret emotional states. For accurate analysis, it is essential to correctly identify and clearly display facial regions (Gülen & Göktaş, 2023). Measurements are based on facial features, as emotions are reflected in the face. For example, happiness can be observed through upward-curving lips or squinting eyes (Matsumoto et al., 2008). Technologies like GPT-4 and MorphCast Emotion AI enable precise emotion measurement, providing valuable insights into students' emotional states during online lessons.

2. METHOD

This research was designed as an observational quantitative analysis aiming to examine students' facial expressions, emotional states, and attention levels during an academic lecture. Data collection was conducted in a natural classroom environment without any interventions or experimental manipulations.

2.1. Research Design

The study adopts a case series design with an observational approach. A case series describes characteristics and outcomes within a group of individuals exposed to a particular condition (or intervention) over a specified period, without a control group (Torres-Duque, Patino, & Ferreira, 2020). This design is used to collect numerical data that reveals patterns, trends, or correlations between variables in a natural setting, without researcher involvement.

2.2. Participants

The study was conducted with 23 undergraduate students enrolled in a tourism education program at a public university. Participants voluntarily took part in the research during a scheduled online course session. All students were informed about the data collection procedures, and ethical approval was obtained prior to implementation. The sample represents a naturally occurring classroom group, allowing for authentic observation of emotional and attentional dynamics in a real instructional context.

2.3. Data Collection Tools and Process

Facial Expression Analysis for Students: Students' facial expressions during the lecture were analyzed using the **MorphCast Emotion AI Video Frames Analyzer**. This advanced facial recognition and emotional analysis software evaluates fundamental emotions (happiness, sadness, anger, fear, surprise, disgust, neutral) and emotional values frame-by-frame from video recordings.

Emotion Analysis for the Academic Instructor: The emotional expressions and sentiment values of the instructor during lectures were analyzed using the **GPT-4 language model**. Text data from the instructor's lecture recordings were processed with GPT-4's natural language processing capabilities to assess emotional tone and sentiment.

Attention Level Measurement for Students: Students' attention levels were determined using data derived from facial expressions and eye movements analyzed by MorphCast software. The software categorized focus levels into "very low," "low," "high," and "very high."

2.4. Data Collection Procedure

Lecture Process: Data collection occurred during standard lectures in the natural classroom environment. Researchers acted as passive observers without intervening in the teaching process. Lectures were conducted once per week over four weeks.

Observation and Recording: Cameras placed at optimal positions in the classroom recorded the facial expressions and behaviors of both the students and the instructor. All recordings adhered to privacy and ethical guidelines.

2.5. Data Analysis

Facial Expression Data Processing: Students' facial expressions were analyzed using MorphCast Emotion AI Video Frames Analyzer. The software processed video frames to determine emotional states and valence values.

Emotion Analysis for the Academic Instructor: Text transcripts from the instructor's lecture recordings were subjected to sentiment analysis using the GPT-4 language model. This analysis provided weekly insights into the instructor's emotional tone and expressions.

Attention Level Analysis: Attention levels of the students were evaluated using MorphCast-derived data and categorized as "very low," "low," "high," or "very high."

Statistical Analyses: Statistical analysis was performed using SPSS (Statistical Package for the Social Sciences). Non-parametric tests, such as the Friedman Test, were used to identify differences between variables. Pairwise comparisons were conducted to detect variations across weeks. Results with a p-value less than 0.05 were considered statistically significant.

2.6. Ethical Considerations

Voluntary Participation: Participants provided informed consent.

Confidentiality and Anonymity: Personal data were anonymized and used solely for research purposes. Data were not shared with third parties.

Preservation of Natural Behavior: Data collection was designed to avoid influencing participants' natural behaviors.

2.7. Limitations

Sample Size: The study was conducted with 23 students representing a single course cohort at one public university. While the AI-based high-resolution emotional and attentional data increased analytical depth, the contextual specificity of the sample may limit broader generalization. Future studies with larger and cross-institutional samples are recommended to enhance external validity.

Duration of Data Collection: The short observation period may not fully reflect long-term emotional and attentional changes.

Accessibility and Accuracy of Records: Limited data recordings and potential biases from software tools pose challenges.

2.8. Methodological Rationale

Pragmatic Factors: The dataset obtained from 23 students was analyzed systematically and efficiently within the available time and technical infrastructure. AI-supported frame-level emotion analysis and attention measurement enabled the extraction of multiple data points from each participant, thereby providing substantial analytical depth independent of sample size. This approach was adopted as a methodological preference emphasizing data density and resolution rather than numerical breadth.

Use of Advanced Technological Tools: The use of MorphCast Emotion AI Video Frames Analyzer and GPT-4 ensured precise and detailed emotional analyses.

Natural Environment Observation: Observing participants in their natural classroom setting without interference ensured the collection of realistic and valid data.

3. FINDINGS

3.1. Students' Facial Expressions and the Emotional Values of the Instructor's Lectures

Table 1 presents the weekly emotional variations in students' facial expressions. Neutral and sadness emotions emerged as the most dominant across the weeks. While neutral emotions increased steadily during the first three weeks, sadness showed a noticeable rise, particularly in the final week.

Negative emotions such as disgust, anger, and fear exhibited fluctuations. Among these, anger and fear remained at relatively low levels during certain weeks. Positive emotions such as happiness and surprise were generally observed at low levels across the study period, without indicating a consistent upward trend.

Although sadness increased categorically in Week 4, composite indices revealed complex fluctuations rather than a uniform directional change. This suggests that categorical emotion percentages and composite valence metrics capture different dimensions of emotional expression. While categorical analysis reflects discrete emotional states, composite metrics provide a broader evaluative perspective on emotional valence.

Table 1
Weekly emotional changes in students' facial expressions

Emotions	Week 1	Week 2	Week 3	Week 4
Disgust	0.61	0.23	3.20	1.95
Fear	3.33	0.25	0.08	0.37
Anger	9.90	4.24	0.23	5.52
Sadness	21.64	23.75	22.25	43.78
Neutral	56.38	67.89	71.50	43.78
Surprise	2.72	1.89	0.19	0.75
Happiness	5.42	1.76	2.54	3.84

Table 2 illustrates the weekly emotional changes observed in the instructor's lectures. Neutral and sadness emotions displayed a fluctuating pattern, with a notable trend toward a more neutral emotional state in the later weeks.

Negative emotions, such as disgust, fear, and anger, spiked significantly in Week 2 but declined in the subsequent weeks. This pattern indicates that the instructor experienced higher levels of stress or discomfort early on, which diminished over time. Positive emotions, including happiness and surprise, also varied across the weeks. A noticeable increase in happiness during Week 3 suggests that the

instructor felt more positive during this particular session. Although sadness percentages increased in Week 4, the overall valence and positivity indices derived from frame-level analysis indicated a statistically significant upward trend. This suggests that categorical emotion frequencies and aggregated valence metrics may reflect different dimensions of emotional expression.

Table 2
Weekly emotional changes in the academician's lecture

Emotions	Week 1	Week 2	Week 3	Week 4
Disgust	5	10	5	5
Fear	15	15	10	10
Anger	10	20	5	5
Sadness	20	25	10	15
Neutral	25	10	30	40
Surprise	10	5	15	10
Happiness	15	15	25	15

Overall, the instructor transitioned from a more stressed and sad emotional state at the beginning to a more neutral and balanced state over time. The simultaneous rise in both happiness and neutral emotions in Week 3 indicates that the instructor experienced greater comfort and positivity during this week's lecture delivery.

Students' Emotional Changes

The upper graph, illustrating the weekly emotional variations of students, displays the percentage distribution of different emotions over four weeks. Neutral emotions were dominant in the initial weeks but decreased significantly by Week 4, where sadness became more prominent. This shift suggests a decline in students' emotional positivity and stability as the weeks progressed.

Instructor's Emotional Changes

The graph representing the instructor's emotional variations during the same period indicates a more balanced distribution of emotions. While neutral and sadness emotions held a significant share, emotions such as disgust, anger, and surprise exhibited greater fluctuations compared to the students. This variance reflects a broader emotional range and potentially higher responsiveness to classroom dynamics.

These findings highlight that while students' emotions leaned towards a negative trajectory over time, the instructor's emotions remained relatively balanced but more variable.

When Fig. 2. Comparison of the emotion graphs of academicians and students is examined, significant changes were observed in the emotional and attention levels of both students and academicians during the four-week course period. Students' facial expressions indicate that they exhibit more negative emotions and some indicators suggest reduced positive emotional expressions in later weeks. The academician, on the other hand, has moved to a more balanced and neutral emotional state over time. These findings may indicate that changes in the course flow and teaching methods are needed to maintain students' interest and attention during the course process. In addition, the academician's effort to increase the attention and motivation of the students with a more positive and motivating approach can improve the overall atmosphere of the course.

3.2. Changes in Students' Attention Levels

An analysis of Appendix Table 1 (Friedman's Two-Way Analysis of Variance by Ranks) revealed that students' attention levels changed significantly over the four weeks ($p < .001$). To identify the source of this difference, Bonferroni-adjusted pairwise comparisons were conducted (Table 3). The results indicate that attention levels in Week 1 were significantly lower than in Weeks 2, 3, and 4 ($p < .001$). Additionally, significant differences were observed between Week 2 and Week 3 ($p < .001$) and between Week 3 and Week 4 ($p < .001$), indicating fluctuations in attention levels across the study period, with a noticeable peak in Week 3 rather than a strictly progressive increase. However, no statistically significant difference was found between Week 2 and Week 4 ($p > .05$), suggesting a relative stabilization of attention levels after the initial increase. Overall, the findings indicate that attention levels improved after the initial week and reached a peak in Week 3, followed by a slight decline in Week 4.

Table 3
Pairwise comparisons

Pairwise Comparisons					
Sample 1-Sample 2	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Mr.**	**Adj. Sig.[and]**
week2-week4	-,004	,006	-,595	,552	1,000
week2-week1	,100	,006	16,545	,000	,000
week2-week3	-,183	,006	-30,437	,000	,000
week4-week1	,096	,006	15,950	,000	,000
week4-week3	,180	,006	29,842	,000	,000
week1-week3	-,084	,006	-13,892	,000	,000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is ,050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Appendix Fig. 1 illustrates the changes in mean attention ranks across four weeks. Although fluctuations are observed between weeks, attention levels reached their highest mean rank in Week 3. Week 2 and Week 4 demonstrated similar mean rank values, while Week 1 remained comparatively lower. Overall, despite minor variations, the pattern indicates improved attention levels after the initial week. Table 4 presents the distribution The “High” and “Very High” attention categories peaked in Week 3, followed by a decline in Week 4. While lower attention categories remained relatively prominent throughout the study period, the mid-period increase in higher attention levels suggests temporary improvements in student engagement rather than a strictly linear upward trend.

Table 4
Segmented attention level shifts

Attention Level	Week 1 (%)	Week 2 (%)	Week 3 (%)	Week 4 (%)	Average (%)	Standard Deviation
Very Low	26.30	30.40	30.10	25.10	27.98	2.32
Low	8.30	13.00	19.80	11.90	13.25	4.16
High	20.20	17.40	24.50	15.60	19.42	3.36
Very High	21.60	20.80	23.50	18.10	21.00	1.94
Missing	23.60	18.40	2.10	29.30	18.35	10.14

3.3. Change in students' stimulus values

An examination of Appendix Table 2 (Friedman’s Two-Way Analysis of Variance by Ranks) revealed statistically significant differences in students’ arousal (stimulation) levels across the four-week period ($p < .001$). This finding indicates that arousal levels varied meaningfully over time and that these differences were not due to random variation.

Pairwise comparisons presented in Table 5 demonstrate that all weekly comparisons yielded statistically significant differences after Bonferroni adjustment ($p \leq .001$). The mean rank values indicate that arousal levels were highest in Week 1 (2.91), declined in Week 2 (2.43), showed a slight increase in Week 3 (2.46), and reached their lowest level in Week 4 (2.20). Overall, the pattern reflects a general downward trend with minor fluctuations rather than a progressive increase. These findings suggest that students’ emotional activation was initially high but gradually decreased as the instructional process progressed.

Table 5
Pairwise comparisons

Pairwise Comparisons Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Mr.	Adj. Sig.[and]
week4-week2	,230	,006	3,649	,000	,000
week4-week3	,252	,006	4,382	,000	,000
week4-week1	,705	,006	11,736	,000	,000
week2-week3	-,023	,006	-3,732	,000	,001
week2-week1	,475	,006	7,887	,000	,000
week3-week1	,452	,006	7,154	,000	,000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is ,050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Appendix Fig. 2 shows that arousal levels varied over the four-week period, with the highest mean rank observed in Week 1 and the lowest in Week 4. Although a slight fluctuation occurred in Week 3, the overall pattern indicates a general decline in arousal levels over time.

Over the four weeks, students' arousal levels, measured through facial expression analysis, were initially high but gradually decreased as the instructional process progressed. This pattern may suggest that initial emotional activation diminished over time. Therefore, incorporating innovative and motivating instructional elements may help maintain students' engagement and emotional activation throughout the learning process.

3.4. Investigation of Valance Values Related to Emotion Values in Facial Expressions

An examination of Appendix Table 3 (Friedman's Two-Way Analysis of Variance by Ranks) revealed statistically significant differences in students' facial expression valence levels across the four-week period ($p < .001$). These findings indicate that emotional valence changed meaningfully over time and that the observed differences were not attributable to random variation.

Pairwise comparisons presented in Table 6 demonstrate statistically significant differences between all week pairs following Bonferroni adjustment ($p < .001$). The mean rank values indicate that valence levels were highest in Week 2 (2.73), declined in Week 3 (2.32), and slightly increased again in Week 4 (2.49), while Week 1 (2.46) showed intermediate levels. Overall, the pattern reflects fluctuations in students'

emotional valence rather than a strictly progressive increase. Although all pairwise comparisons were statistically significant (p < .001), the changes across weeks do not follow a linear upward trajectory.

Table 6
Pairwise comparisons

Pairwise Comparisons Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Mr.	Adj. Sig.[and]
week3-week1	,138	,006	22,624	,000	,000
week3-week4	-,164	,006	-26,965	,000	,000
week3-week2	,408	,006	66,911	,000	,000
week1-week4	-,026	,006	-4,341	,000	,000
week1-week2	-,270	,006	-44,286	,000	,000
week4-week2	,244	,006	39,946	,000	,000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is ,050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

The findings presented in Table 6 demonstrate that students' emotional valence levels differed significantly across the four weeks. Pairwise comparisons confirm statistically significant differences between all weeks; however, the direction of change reflects a non-linear pattern rather than a strictly progressive increase. Although the lowest levels were observed in the initial week and the highest levels were recorded in Week 4, intermediate fluctuations indicate dynamic shifts in emotional valence throughout the instructional period.

Appendix Fig. 3 illustrates these fluctuations in mean valence ranks, supporting the interpretation that emotional positivity followed a dynamic trajectory rather than a continuous upward trend.

3.5. Investigation of Positivity Values Related to Emotion Values in Facial Expressions

An examination of Appendix Table 4 (Friedman's Two-Way Analysis of Variance by Ranks) revealed statistically significant differences in positivity levels across the four-week period (p < .001). This finding indicates that students' positive emotional expressions varied meaningfully over time.

Pairwise comparisons presented in Table 7 demonstrate statistically significant differences between all week pairs following Bonferroni adjustment (p < .001). The mean rank values indicate that positivity levels were highest in Week 1 (2.86) and gradually declined across the subsequent weeks, reaching their lowest level in Week 4 (2.14). Week 2 (2.70) and Week 3 (2.30) showed intermediate values, reflecting a

steady downward trend over time. Although all pairwise comparisons were statistically significant ($p < .001$), the pattern represents a progressive decrease rather than an increase in positivity levels throughout the instructional period. Overall, the findings indicate a gradual decline in positive emotional expressions over the four-week period. Rather than demonstrating increasing emotional positivity, the results suggest that students' positive facial expressions became less frequent as the instructional process progressed.

Table 7
Pairwise comparisons

Pairwise Comparisons					
Sample 1-Sample 2	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Mr.**	**Adj. Sig.[and]**
week4-week3	,164	,006	26,935	,000	,000
week4-week2	,566	,006	92,802	,000	,000
week4-week1	,720	,006	118,060	,000	,000
week3-week2	,402	,006	65,867	,000	,000
week3-week1	,556	,006	91,126	,000	,000
week2-week1	,154	,006	25,259	,000	,000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is ,050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

When Table 7 is examined, it can be concluded that the positivity levels of the students based on their facial expressions differ week by week.

Appendix Fig. 4 illustrates the changes in mean positivity ranks across the four-week period. The figure clearly demonstrates a gradual decline in positivity levels over time. The highest mean rank was observed in Week 1, followed by a steady decrease in Weeks 2 and 3, with the lowest level recorded in Week 4. This pattern indicates that students' positive emotional expressions diminished progressively throughout the instructional period rather than showing an upward trend. Although all pairwise comparisons were statistically significant, the visual pattern presented in the figure confirms a consistent downward trajectory in positivity levels across weeks. This decline may suggest that initial positive emotional engagement decreased as the instructional process progressed.

CONCLUSION AND DISCUSSION

This study offers significant educational insights by analyzing emotional states and attention levels of both students and the instructor over a four-week lecture series. The findings reveal how emotional

responses evolved over time for both groups, providing opportunities to develop new approaches for enhancing educational processes.

Emotional Changes in Students and the Instructor

Students' facial expressions were predominantly characterized by neutral and sadness emotions. Neutral expressions increased during the first three weeks, while sadness rose noticeably in the final week. Although categorical happiness and surprise percentages remained relatively low, the composite emotional indicators (attention, arousal, valence, and positivity) did not demonstrate a uniform upward trend. Instead, the findings revealed fluctuating and, in some cases, declining patterns over time.

Changes in Attention and Arousal Levels

Attention Levels

Students' attention levels varied significantly across weeks. Attention was lowest in Week 1, increased and peaked in Week 3, and then slightly declined in Week 4. This pattern reflects a mid-period enhancement rather than a continuous increase.

Arousal Levels

Arousal levels demonstrated a gradual decline over the four-week period. The highest activation was observed in Week 1, followed by a steady decrease toward Week 4. This pattern may indicate diminishing emotional stimulation or adaptation over time.

Changes in Valence and Positivity Levels

Valence levels fluctuated significantly across weeks. The highest valence was observed in Week 2, followed by a decrease in Week 3 and a partial recovery in Week 4. This non-linear pattern suggests dynamic emotional shifts rather than progressive improvement.

Positivity levels demonstrated a consistent decline across the four weeks. The highest positivity was observed in Week 1, and levels gradually decreased toward Week 4. This downward trajectory indicates that positive emotional expressions diminished over time.

Educational Implications

These findings underscore the critical role of emotional and attentional factors in evaluating and improving educational processes. Insights from such studies can benefit both instructors and students in the following ways:

Evaluating and Improving Teaching Methods and Content

Instructors can monitor emotional and attentional changes to identify effective teaching methods and content. For example, the peak in attention observed in Week 3 suggests that instructional strategies

implemented during this period may have temporarily enhanced student engagement.

Enhancing Student Motivation and Engagement

Variations in students' emotional responses reflect their interest and motivation levels. During periods of increased negative emotions, instructors can implement motivational activities or tailor lesson content to students' interests. The instructor's positive emotional expressions can also boost student motivation.

Personalized Learning Experiences

Individual emotional and attentional profiles can be used to design personalized learning experiences. Differentiated teaching strategies can address specific student needs, while the instructor's emotional awareness plays a vital role in fostering a supportive learning environment.

Instructor Performance Evaluation and Professional Development

The instructor's emotional state can significantly impact students' emotional and attentional responses. Enhancing instructors' emotional intelligence, classroom management, and communication skills can contribute to their professional growth and improve teaching quality.

Integration of Educational Technologies and Real-Time Feedback

Technologies that analyze facial expressions and emotional states can support real-time feedback systems. By monitoring emotional and attentional states, instructors can make immediate adjustments during lessons, creating a more dynamic and effective learning environment.

Recommendations

This study highlights the importance of emotional and attentional factors in shaping educational outcomes. Both educators and institutions can benefit from increased awareness of these areas to improve instructional strategies.

Recommendations for Instructors

Emotional Awareness and Management

Instructors should recognize how their emotional state impacts students and develop emotion management skills to foster a positive classroom atmosphere.

Interactive and Engaging Teaching Methods

Using interactive methods, technology-supported tools, group work, and project-based learning can enhance student motivation and attention.

Real-Time Feedback Systems

Incorporating systems to monitor emotional and attentional states can help instructors adjust their approach dynamically during lessons.

Recommendations for Educational Institutions

Reviewing Educational Programs

Curriculum and lesson plans should be redesigned to address the emotional and attentional needs of both students and instructors.

Professional Development and Training

Providing training on emotional intelligence, classroom management, stress management, and technology integration can enhance instructors' skills.

Comprehensive Evaluation Systems

Incorporating emotional and attentional factors into student and instructor evaluations can provide a holistic view of the educational process.

Conclusion

This study investigated week-to-week changes in students' attention and emotional states during online tourism education using facial expression analysis. The findings revealed statistically significant differences across all measured dimensions (attention, arousal, valence, and positivity) over the four-week period. Attention levels demonstrated significant variation, with the lowest levels observed in Week 1 and a peak in Week 3, followed by a slight decline in Week 4. This pattern indicates a mid-period increase rather than a continuous upward trend. Arousal levels showed a general downward trajectory across the four weeks. The highest activation was observed in Week 1, and levels gradually decreased over time, suggesting diminishing emotional stimulation as the instructional process progressed. Valence levels fluctuated throughout the study period. The highest mean valence was observed in Week 2, followed by a decline in Week 3 and a partial recovery in Week 4. These findings indicate dynamic emotional shifts rather than progressive enhancement. Positivity levels demonstrated a consistent decline over time, with the highest levels in Week 1 and the lowest in Week 4. This downward trend suggests that positive emotional expressions decreased as the instructional period advanced. Overall, the results highlight that emotional and attentional responses in online learning environments are dynamic and non-linear. Overall, the results highlight that emotional and attentional responses in online learning environments are dynamic and non-linear.Rather than demonstrating continuous improvement, the findings reveal fluctuating patterns that may reflect changes in engagement, adaptation, or instructional dynamics over time.

Declarations

Data availability

The datasets generated and/or analysed during the current study are not publicly available due to privacy and ethical considerations associated with facial image recordings obtained during online course sessions. However, anonymized and processed analytical data supporting the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare that they have no competing interests.

Ethical Approval

Ethical approval for this study was obtained from the Social and Human Sciences Research Ethics Committee of Balıkesir University (Meeting No: 2024/09, Date: 04 October 2024). The committee reviewed the research protocol and determined that the study complied with the ethical standards required for research involving human participants.

All procedures performed in this research involving human participants were conducted in accordance with the ethical standards of the institutional research committee and with internationally accepted ethical principles for research involving human subjects, including the principles outlined in the Declaration of Helsinki.

Informed Consent

Written informed consent was obtained from all participants prior to the data collection process. Participants consisted of undergraduate students enrolled in an online tourism course conducted at the Faculty of Tourism of Balıkesir University. Before participating in the study, the students were informed in detail about the objectives of the research, the procedures involved in the data collection process, the use of video recordings for the analysis of facial expressions and attention levels, and the measures taken to ensure the confidentiality and protection of their personal data. The lecture recordings used as the primary data source in this study were obtained during online course sessions by the authors. Data collection was conducted between 24 February 2025 and 21 March 2025 during the online course sessions.

Participation in the study was entirely voluntary, and participants were informed that they could withdraw from the study at any time without any academic or personal consequences. All participants provided written informed consent and agreed to the use of anonymized data for scientific research and publication purposes.

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Author Contribution

B.Ö. (Bayram Özer) and V.D. (Vokan Duran) contributed to the study conception, design, data collection, analysis, and drafting of the manuscript. M.O. (Musa Oflaz) was responsible for survey administration, summarizing the findings, and preparing the discussion and recommendations. All authors critically reviewed the manuscript and approved the final version for submission.

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Figures

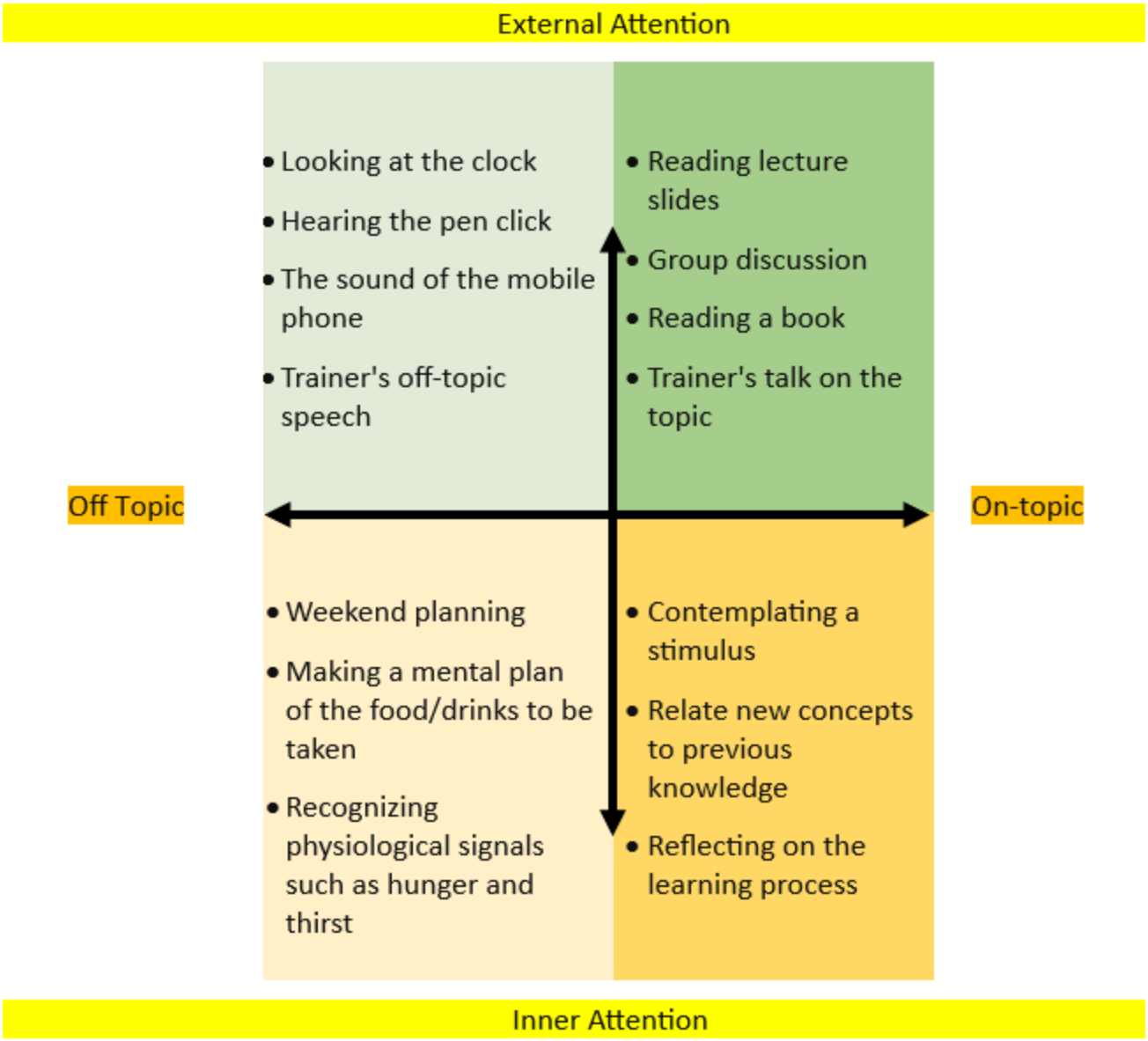


Figure 1

Mindfulness-related classroom scenarios

Source: Keller et al., 2020



Figure 2

Comparison of the emotion graphs of academicians and students

Supplementary Files

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- SuplemantaryFileAppendixfigure1.2.3.4..docx
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