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Multichannel assessment of cognitive load and emotions with pedagogical avatars in higher education

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ABSTRACT

Integrating multimodal devices (eye tracking, electroencephalography [EEG], and galvanic skin response [GSR]) enables the objective assessment of cognitive and emotional processes during controlled tasks. In higher education multimedia contexts, such measures can inform the adaptive design of educational interfaces. This study examined the processing of avatar images expressing positive (surprise, joy) and negative (sadness, fear) emotions across different user groups (final-year university students, novice university lecturers, and experienced university lecturers), while also considering gender effects. Forty-eight participants completed a visualisation task while physiological indicators derived from EEG (engagement, memorisation, valence, workload), GSR (impact), and eye tracking (number of visits and dwell time) were recorded for relevant and non-relevant areas of interest. Significant differences emerged for surprise, with students showing more visits to non-relevant areas than lecturers members. For joy, final-year university students exhibited longer dwell times on relevant areas than experienced lecturers. No differences by professional group were found for sadness or fear. Regarding gender, women showed higher valence and workload in the joy condition, as well as higher memorisation and longer dwell times in the sadness condition. Based on these findings, adaptive adjustments to avatar design are proposed to better align with users' cognitive and emotional profiles.

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1. Introduction

Analysis of cognitive load is fundamental for understanding learning performance and effectiveness in technology-mediated environments. Cognitive Load Theory (CLT) posits that working memory has a limited capacity for processing information simultaneously (Chandler and Sweller 1991). This framework distinguishes three types of cognitive load: intrinsic, associated with task complexity and learner expertise; extraneous, related to the design and presentation of material; and germane, linked to the cognitive effort devoted to constructing and integrating schemas into long-term memory (Van Merriënboer and Sweller 2010). Empirical evidence indicates that minimising unnecessary extraneous load and promoting germane load optimises the use of cognitive resources and enhances learning outcomes (Houssein, Hammad, and

Ali 2022; Liu and Cui 2025), with this combination being a positive predictor of task success (Lee et al. 2020; Wang et al. 2023). Moreover, prior experience facilitates more efficient cognitive load management, reducing the mental effort required for task execution (Armougum et al. 2025). For example, germane cognitive load is activated when a student interacting with an educational avatar actively integrates the information provided by the avatar with their prior knowledge, for instance, by reorganising problem-solving strategies or refining existing mental models based on the avatar's emotional feedback. In this case, cognitive effort is devoted to schema construction and automation rather than task complexity.

These principles align with models of working memory, particularly Baddeley's framework (Baddeley 2007; Baddeley et al. 2020), which conceptualises working memory as a dynamic system responsible for the active

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manipulation of information and its interaction with long-term memory. Given the limited capacity of working memory (Ba and Hu 2023; Chandler and Sweller 1991), design of educational materials and digital learning environments must explicitly consider these limits to avoid cognitive overload and promote effective information processing.

In this context, the use of non-invasive technological tools has advanced the study of cognitive processing during learning tasks. Techniques such as eye tracking, galvanic skin response (GSR), and electroencephalography (EEG) provide objective measures of cognitive effort, attention, and emotional activation (Picard et al. 2004; Xue, Wang, and Qiu 2025). Eye tracking allows identification of visual attention patterns and estimation of cognitive load through metrics such as fixations, saccades, and pupil diameter (Duchowski 2020; Rayner 2009; Sun and Nembhard 2025), while GSR and EEG provide information on emotional arousal, stress, and cognitive fatigue (Ronca et al. 2025; Zhou, Xu, and Zhang 2025). Recent studies highlight that integrating multichannel recordings offers a more precise characterisation of information processing during learning than single measures, especially when combined with subjective instruments such as the NASA-TLX scale (Almukhtar et al. 2025; Hart 2006).

Beyond cognitive processes, emotions play a fundamental role in learning and student engagement. Empirical evidence shows that positive emotions are associated with higher levels of motivation, cognitive effort, and task persistence, whereas negative emotions can interfere with working memory and decision-making processes, affecting learning performance (Dubovi 2022; Li et al. 2025). In multimedia learning environments, affective computing and the use of educational avatars are promising strategies for tailoring interaction

to users' emotional states, enhancing engagement, and providing a more personalised learning experience (Picard et al. 2004; Saavedra et al. 2025). Nevertheless, despite growing interest in these approaches, there is still only limited empirical evidence analysing the integrated relationship between emotions, cognitive load, and physiological responses in interactions with educational avatars, especially from a multimodal perspective.

To address this gap, the main objective of the present study was to monitor and subsequently analyse how different profiles within the university community (final-year university students, novice university lecturers, and experienced university lecturers) processed images of an avatar expressing positive and negative emotions. Monitoring was conducted using a combination of eye tracking, GSR, and EEG measures. The ultimate goal is to illustrate how integrated analysis of objective physiological signals can contribute to the adaptive design of educational avatars, tailored to users' cognitive and emotional responses, in order to optimise the effectiveness of digital learning environments.

Figure 1 summarises the relationship between memory stores, phases of information processing, and the cognitive and metacognitive strategies applied during task performance.

2. Application of technology for monitoring information processing

Over the past decade, advances in neuroscience and non-invasive technologies have enabled the analysis of information processing and cognitive activity during learning tasks, in both clinical and neurotypical populations. EEG stands out among these techniques as it

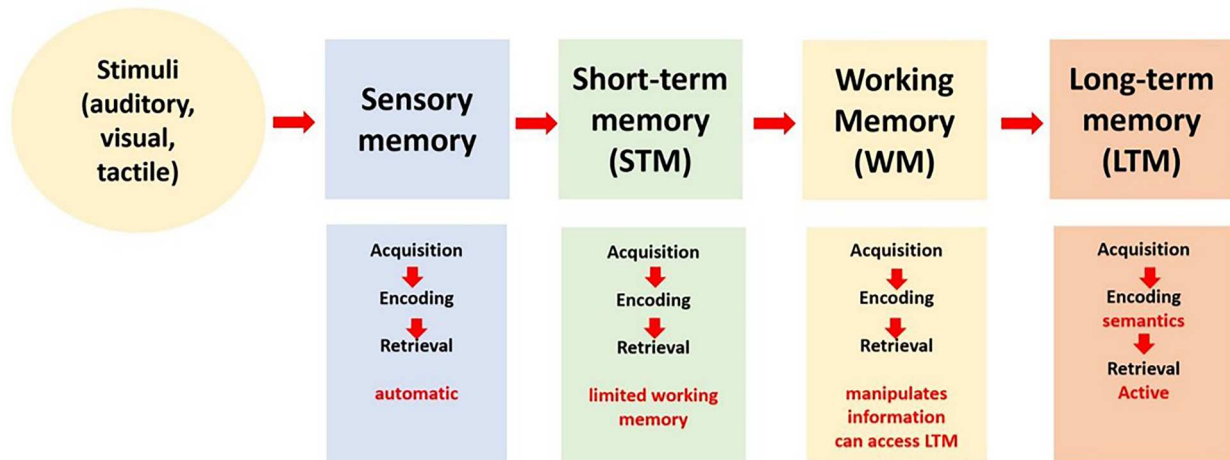


Figure 1. Relationship between different types of memory and information processing.

allows the recording of brain electrical activity and the analysis of cognitive processes through event-related potentials, providing precise information about how the brain responds to specific stimuli (Baddeley et al. 2020). Alongside EEG, other non-invasive devices such as eye tracking and GSR have become important tools for studying human cognition in educational and technological contexts (Xue, Wang, and Qiu 2025). They can also be used to provide information about emotion, a complex psychophysiological phenomenon triggered by external stimuli that profoundly influences cognitive processes, decision-making, and social behaviour. Emotion recognition has broad potential applications in both healthcare and education (Qu et al. 2025).

Eye tracking is widely used in multimedia learning environments to analyse cognitive load imposed by educational materials and visual attention patterns in different types of learners (X. Liu and Cui 2025; Yu, Androsov, and Yan 2025). These measures allow identification of attentional behaviours within pre-defined areas of interest (AOIs), providing objective data on visual exploration (Shao et al. 2025; Xue, Wang, and Qiu 2025). Several studies have shown that metrics such as the number and duration of fixations, saccade amplitude, and pupil diameter are associated with content difficulty, information search efficiency, and the cognitive load experienced by learners (Duchowski 2020; Rayner 2009; Sun and Nembhard 2025). In particular, mean fixation duration has been linked to extraneous cognitive load and individual working memory capacity (Zu et al. 2018).

In this context, Affective Computing (AC) has shown remarkable potential for enhancing human-computer interaction in educational settings. Pioneering studies indicate that AC-based systems generate higher levels of engagement, cognitive effort, and emotional impact compared to conventional technologies (Picard et al. 2004), influencing unconscious responses relevant to personalising the learning experience (Saavedra et al. 2025). Presenting motivating educational materials is thus key to promoting student engagement (Sun and Nembhard 2025).

GSR devices allow evaluation of autonomic nervous system (ANS) activation during interactions with educational materials, distinguishing between tonic and phasic responses associated with the emotional and cognitive impact of stimuli (Ronca et al. 2025; Saavedra et al. 2025). Recent evidence indicates that integrating multichannel recordings – combining eye tracking, GSR, and EEG – provides a more precise characterisation of information processing during learning tasks,

especially when complemented with subjective measures such as the NASA-TLX scale (Bell et al. 2022; Hao et al. 2025; Hart 2006). Combining eye tracking, GSR, and EEG signals produces better descriptions of emotional states than individual signals, providing more detailed, more accurate metrics.

With regard to the GSR signal, the Emotional Impact construct measures the quantity and intensity of abrupt changes in emotional state generated by a stimulus, event, or task, reflecting surprising, emotional, or stress responses. It is expressed as a percentage: 0% indicates no impact, and 100% corresponds to the calibration response, which can be exceeded if the reaction surpasses that value. The formula is presented below.

$$\text{Impact} = \frac{\text{number of peaks} \times \text{average intensity of peaks}}{\text{calibration value}} \times 100$$

In the EEG signal, the constructs of engagement, valence, memorisation, and workload are distinguished. Engagement is defined as the degree of involvement or connection of the participant with a stimulus or task. Engagement is a broader construct than attention, as a person may be attentive without the content being relevant or motivating. It is expressed as a percentage: values near 0% indicate no connection to the stimuli, while values close to 100% reflect high involvement. The extraction formula is presented below:

$$\text{Engagement Index} = \frac{\beta}{\alpha + \theta}$$

Where

Beta (β) bands = 13 – 30 Hz, associated with states of alertness and concentration

Alpha (α) bands = 8 – 13 Hz, High α indicates relaxation while low indicates activation

Theta (θ) bands = 4 – 8 Hz, θ increases with tiredness, fatigue, or high cognitive load

Valence measures affective attraction or reaction to a stimulus, ranging from positive/pleasant to negative/unpleasant. It is expressed as a percentage, where 100% corresponds to the calibration value and can be exceeded if the response is greater than the reference. Valence is calculated from frontal alpha asymmetry (FAA). A decrease in α indicates greater cortical activation. The extraction formula is presented below:

$$\text{FAA}_{\infty} = \ln(\alpha \text{ right}) - \ln(\alpha \text{ left})$$

Memorisation reflects the intensity of cognitive processes involved in encoding and retaining information. It is expressed as a percentage: 0% indicates a low

probability of recall, and 100% indicates a high probability. It is estimated through a weighted combination of Theta (θ), Alpha (α), and Gamma (γ) bands in the frontal region. The extraction formula is presented below:

$$\text{Memory} = \omega_1 + \theta_{\text{front}} - \omega_2 * \alpha_{\text{front}} (\omega_3 * \gamma_{\text{front}})$$

where ω are weighting coefficients assigned to the frequency band.

Workload indicates the level of concentration and use of cognitive resources during interaction with a stimulus or task. Values near 0% reflect distraction, while values close to 100% indicate high levels of attention. It is calculated as:

$$\text{Workload } \alpha = \frac{\theta_{\text{front}}}{\alpha_{\text{front}}}$$

where α is the Alpha band and θ is the Theta band.

Overall, the multimodal approach contributes to a deeper, more robust understanding of the cognitive, attentional, and emotional processes involved in multimedia learning (Almukhtar et al. 2025; Saiz-Manzanares, Marticorena-Sánchez, Saez-García et al. 2024). Considering this evidence is fundamental for designing functional, engaging, and emotionally adaptive educational materials, minimising unnecessary extraneous cognitive load while promoting relevant mental effort for learning (Plass and Kalyuga 2019; Xue, Wang, and Qiu 2025). Furthermore, using advanced multichannel data analysis techniques allows user responses to be monitored and mapped, facilitating personalisation of educational interventions in virtual learning environments (Sáiz-Manzanares et al. 2025). Consequently, more studies are needed to analyse multimodal emotion recognition based on physiological signals (Ding, Ma, and Li 2025).

3. Importance of emotions in information processing

In technology-mediated learning contexts, learners' emotional responses to educational materials are crucial for engagement and learning effectiveness (Sáiz-Manzanares, Saiz-Manzanares, Marticorena-Sánchez, Martín Antón et al. 2024). Engagement encompasses behavioural, emotional, and cognitive components that evolve throughout the learning process (Dubovi 2022; D'Mello 2017). This means that integrating multimodal data, such as eye tracking, EEG, and other physiological sensors, allows for richer, more accurate capture of cognitive and affective processes during learning tasks, overcoming the limitations of single-mode methods

(Azevedo and Gašević 2019). The multimodal approach enables simultaneous analysis of multiple dimensions of learner behaviour in technological environments.

Accordingly, using multichannel devices allows for more precise analysis of emotions experienced by different types of learners, such as novice and experienced users (Ba and Hu 2023). Empirical evidence shows that positive emotions (e.g. joy or calm) are associated with higher levels of motivation, engagement, and cognitive effort, while negative emotions (e.g. fear or sadness) are often linked to stress, frustration, and lower learning performance (Dubovi 2022; Schachter and Singer 1962; Skinner and Zimmer-Gembeck 2016). Techniques such as eye tracking can be used to infer attentional and cognitive processes, as a higher frequency or longer duration of fixations may reflect more intense cognitive processing or greater task difficulty (Alemdag and Cagiltay 2018; Sáiz-Manzanares, Marticorena-Sánchez, Martín Antón, et al. 2024b). This can be complemented by GSR providing information on emotional and cognitive activation (Parong and Mayer 2021; Poupard et al. 2025), while EEG allows detection of cognitive fatigue and responses associated with anxiety, stress, or interest (Cao, Zhao, and Sun 2025; Liu et al. 2025; Wei et al. 2025; Zhou, Xu, and Zhang 2025).

Emotional processing involves the activation and retrieval of memories, generating additional cognitive load that may affect working memory performance and decision-making during learning (Li et al. 2025; Zenia et al. 2025). In particular, negative emotional stimuli tend to impair working memory functioning compared to positive stimuli, although these effects depend on the timing of information processing (Baddeley 2012; Li et al. 2025). These findings are especially relevant in learning environments that require high precision, such as surgical training or neurorehabilitation, where emotional and cognitive regulation is critical (Almukhtar et al. 2025; Azadi and García-Peñalvo 2025; Liu et al. 2025; Sáiz-Manzanares et al., 2024a). However, studies highlight gaps in understanding the relationship between emotions and physiological responses, reinforcing the need for integrated multichannel records (Ba and Hu 2023; D'Mello 2017).

More specifically with regard to processing images representing different emotions, eye-tracking studies have consistently shown that when observing a face, people focus most of their fixations on the eyes (primary source of information) and the mouth (secondary information, relevant for expressions and communication). The region formed by the eyes–nose–mouth triangle is where visual attention is concentrated, indicating that these areas are the most informative. The selection of

this region as the focus of analysis is supported by preferential visual attention, specialised neural representation (amygdala, hippocampus), cortical networks dedicated to facial processing, retinotopic tuning, and the social and emotional relevance of the eyes and mouth. Overall, evidence suggests that the eyes–nose–mouth triangle constitutes the functional core of facial information relevant for perception, social cognition, and emotion recognition (Calvo et al. 2018; Liu et al. 2025; Thompson et al. 2019).

In the context of online learning, conversational agents and anthropomorphised avatars have shown potential for increasing emotional engagement, particularly when expressing positive emotions, whereas neutral or negative expressions are associated with lower motivational impact (Dubovi 2022; Kumar 2024; Yu et al. 2024). Based on this evidence, the present study aimed to analyse how images of an avatar expressing positive and negative emotions are processed in university users with different levels of experience (final-year university students vs. experienced lecturers), with the goal of adapting the avatar design according to their cognitive and physiological responses.

Studies have reported gender differences in multichannel integration metrics from recognition of emotion-representing images, particularly differentiating cognitive processing for negative images and eye-tracking metrics related to the eyes–mouth triangle (Bao et al. 2019; Bilalpur et al. 2020). Men tended to show lower arousal and/or comfort in response to negative images than women (Li et al. 2024). However, other studies found no statistically significant gender differences but did report differences in viewing duration, with young adults spending more time than older adults (González-Gualda et al. 2024).

Finally, it is important to note that cognition and emotion are interrelated processes sharing neural resources, such as front-limbic networks. Therefore, EEG and GSR devices do not capture emotion or cognition in isolation, but rather the physiological manifestations of functional states that often combine both.

Considering the state of the art, the main objective of this study was to analyse the cognitive and emotional processing in different higher education groups (university students and lecturers with varying levels of experience: novice and experienced) when viewing images of an avatar expressing positive and negative emotions. The primary purpose was to demonstrate how the combination of a simple visual task – looking at positive and negative emotional images of an avatar – and integrated physiological signal devices allows capture of objective indicators of cognitive and emotional processing, contributing to the validation of adaptive personalisation

strategies tailored to the specific characteristics of each group.

Specific objectives were:

Apply integrated multichannel devices – eye tracking, GSR, and EEG – to objectively analyse the cognitive and emotional load experienced by different groups (final-year university students, novice and experienced lecturers; gender will also be considered) during exposure to images of an avatar expressing positive and negative emotions.

Evaluate differences in visual attention to relevant and non-relevant Areas of Interest (AOIs) depending on the emotions expressed by the avatar, considering the facial triangle region as relevant and any point outside this region as non-relevant.

Based on findings about cognitive load and emotional perception, propose recommendations to adjust the avatar design as a pedagogical resource tailored to each group.

Research questions (RQs):

RQ1. Are there significant differences in relevant AOIs (facial triangle region) in relation to physiological indicators – Engagement, Impact, Memorization, Valence, Workload, number of visits, and visit duration – according to participant type (final-year university students, novice university lecturers, and experienced university lecturers), the emotion expressed by the avatar (positive or negative), and participant gender?

RQ2. Are there significant differences in non-relevant AOIs (outside the facial triangle) in relation to the same physiological indicators, according to participant type, the emotion expressed by the avatar, and participant gender?

4. Method

4.1. Participants

A convenience sample of 51 participants was recruited from the university community in the field of health sciences, a field in which there are traditionally more women than men. However, three participants were excluded due to device calibration issues. Consequently,

Table 1. Description of sample characteristics.

Group	N	Gender		Age range (%)		
		Female	Male			
1	22	14	8	1 (95.5%)	2(4.5%)	
2	16	10	6	1(81.3%)	2 (12.5%)	3 (6.3%)
3	10	5	5	2(20%),	3 (50%)	4 (30%)

Note: Group 1 = final-year university students; Group 2 = novice university lecturers, with less than 4 years of professional experience; Group 3 = experienced university lecturers with more than 9 years of professional experience.

the final sample consisted of 48 subjects. Table 1 shows the characteristics of the final sample.

Although the sample size may be considered moderate from a strictly between-subjects perspective, it is adequate in the context of psychophysiological studies integrating multichannel signals such as eye tracking, GSR, EEG. This type of research requires highly controlled experimental procedures, prolonged recording sessions, and intensive data processing, which puts practical limits on the number of participants but increases analytical sensitivity and the richness of intra-individual information.

This means that similar sample sizes are common in the literature on affective computing and biomarker-based neuroeducation, and such samples have been shown to be sufficient to identify differential patterns in objective cognitive and emotional indicators. Specifically, in the field of EEG and event-related potentials (ERP), systematic reviews indicate that the average sample size in published studies is relatively small, with a mean of approximately 35 participants and a mode close to 20, reflecting the methodological complexity associated with acquiring and processing high-quality physiological data in controlled experimental settings (Morales et al. 2025).

Furthermore, voluntary participation and the requirement for strict ethical controls make the application of probabilistic sampling procedures challenging in this type of quasi-experimental design.

4.2. Instruments

- a. The NASA-TLX scale is a subjective assessment tool that measures the workload perceived by a person when performing a task. NASA-TLX assesses six dimensions: Mental load (mental and perceptual effort required); Physical load (physical effort

required); Time load (time pressure or urgency to complete the task); Performance (subjective assessment of success in performing the task); Effort (total amount of physical and mental work required), and Frustration level (feelings of insecurity, stress, or irritation). Each dimension is rated on a scale of 0–100. The scale can be applied in a weighted or unweighted (raw) version. In this study, we used the weighted version, in which each participant compares each pair of dimensions (15 in total) and chooses which of the two they think was the most important workload for the task, giving the weighting value. Next, the participant rates each of the six dimensions on a scale of 0–100. Subsequently, the score for each dimension is multiplied by its weighting factor.

$$NASA - TLX \text{ weighted} = \frac{\sum_{i=1}^6 (P_i \times W_i)}{\sum_{i=1}^6 W_i}$$

Where P_i = score assigned to dimension i on a scale from 0 to 100, W_i = weight of dimension i , corresponding to the number of times it was selected as the most important in the 15 pairwise comparisons; $W_i = 15$.

- b. Bitbrain Headband Device (2025). Dry-sensor EEG optimised to monitor emotional and cognitive states in real-world applications. The Diadem system was developed with 12 dry sensors located in specific brain areas (prefrontal, frontal, parietal, and occipital) for assessing emotional and cognitive states. Its active shielding and stable mechanical design provide robustness and signal quality, even during movement or extended recording periods. It has a 3rd order bandpass filter, with frequencies from 1 to 30 Hz, and a notch filter. An image of the device is shown in Figure 2.

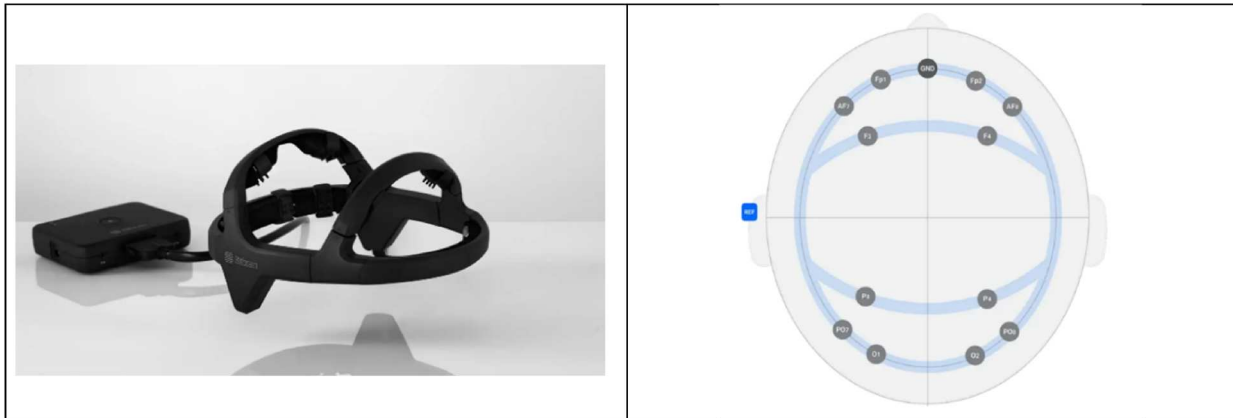


Figure 2. Bitbrain headband device, free-access images extracted from Bitbrain.

- c. **Bitbrain Ring Device.** The Ring is a mobile device for monitoring biological signals, measuring EDA and cardiovascular activity (BVP). It is lightweight and comfortable, with two key biosensors for basic assessment of emotional states (GSR – EDA and BVP – heart activity) and a three-axis accelerometer (ACC) to estimate motion-related noise from hand movements. Its stable mechanical design provides good robustness and signal quality, even during movement or extended recording periods. It has a 2nd order bandpass filter, with frequencies from 0.5 to 2 Hz. An image of the device can be found in [Figure 3](#).
- d. **Tobii Screen-Mounted Eye-Tracking Device.** The study used the Tobii Pro Lab v. 24.21.435 (x64), integrated with EEG and GSR signals from the other Bitbrain devices. The system operated with a gaze sampling frequency of 60 Hz, an accuracy of 0.45°, and a precision (RMS under optimal conditions) of 0.26°. An example of the integrated application of the devices described in b, c, and d is shown in [Figure 4](#).
- e. **Avatar Images.** Four images were used, created ad hoc with the Bitmoji application to represent different emotions (Sáiz-Manzanares 2024), they are freely available at <http://hdl.handle.net/10259/10225>. This

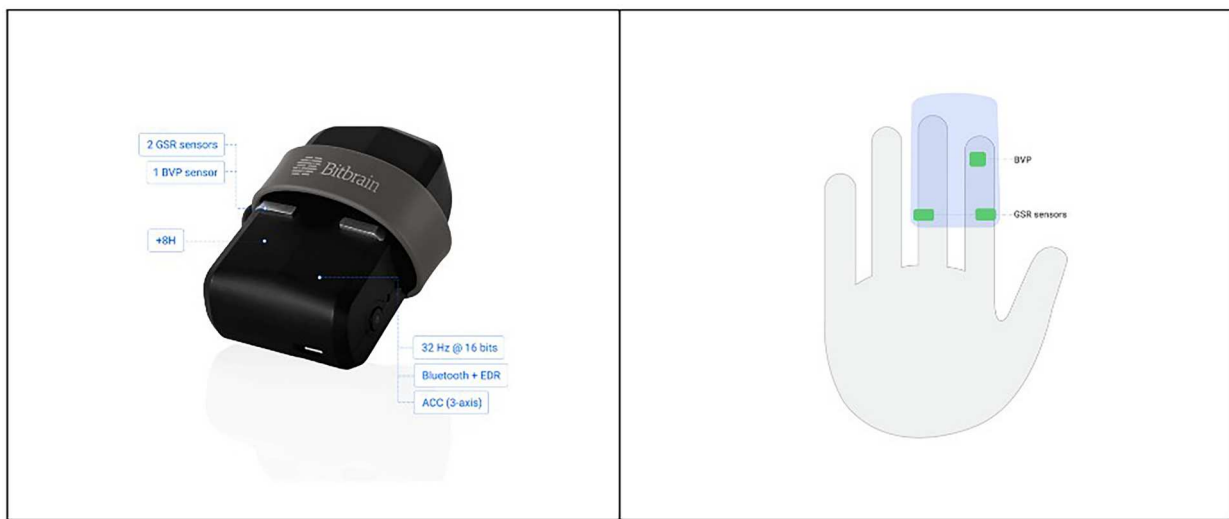


Figure 3. Bitbrain Ring device, free-access images extracted from Bitbrain.

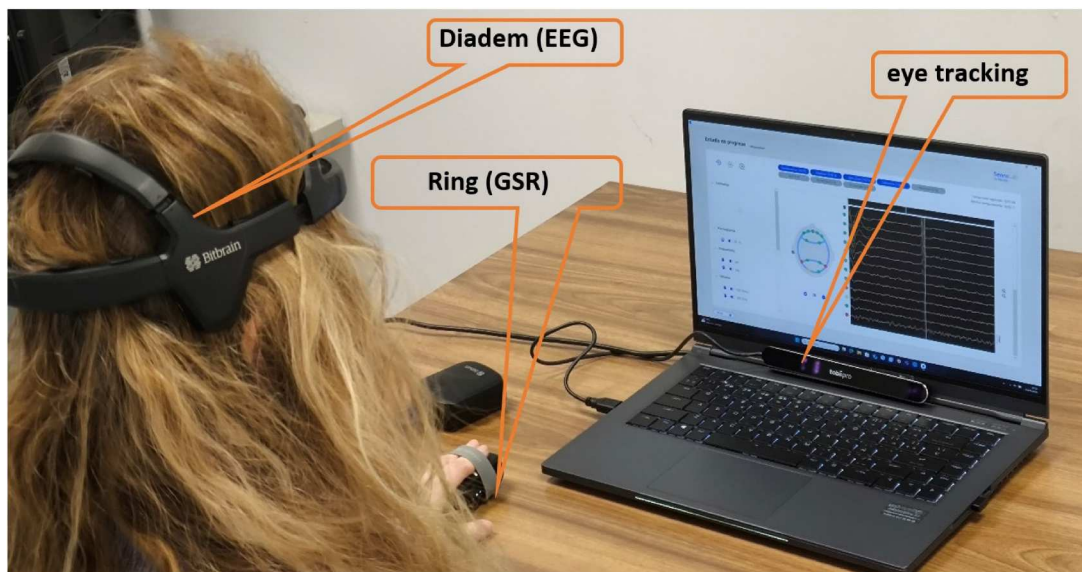


Figure 4. Bitbrain Diadem and Ring devices and screen-mounted eye-tracking Tobii Pro Lab v. 24.21.435 (x64), image from the authors.

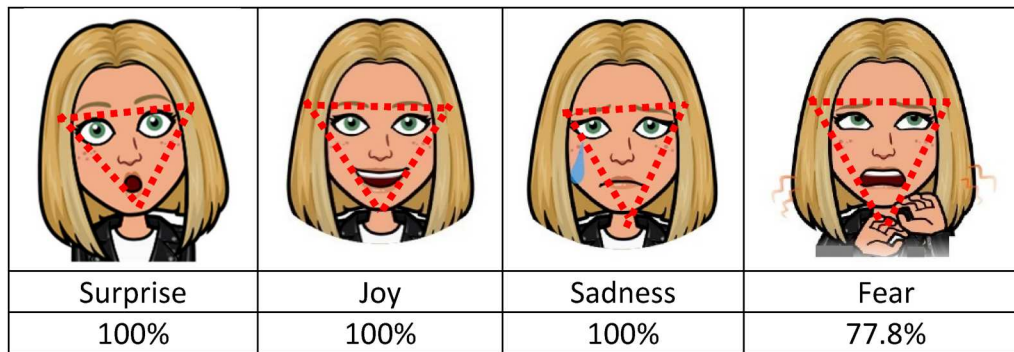


Figure 5. Emotion images and relevant AOIs within the facial triangle.

Note: The relevant AOI was the eye–nose–mouth triangle.

application was chosen because it is commonly used in studies applying physiological metrics for emotion analysis in virtual classroom settings (Hastuti 2024; Santosa and Wahyuni 2024). The emotions in the images were categorised via an expert panel, involving nine professionals in emotional psychology analysing the images. Figure 5 shows the images used, their emotional categorisation, and the percentage of agreement between the experts. Additionally, the relevant AOI for each image was defined with respect to the facial triangle (eyes–nose–mouth). Images were classified as positive (Joy and Surprise) and negative (Sadness and Fear).

- f. Metrics from the integrated signals obtained from the Bitbrain devices and eye tracking. Table 2 describes the metrics in relation to the device used in the integrated signal.

4.3. Procedure

First, approval for the study was obtained from the Bioethics Committee of the University of Burgos (No. IO 5/2024). Subsequently, written informed consent was obtained from all participants; participation was voluntary and without any remuneration. Next, the weighting portion of the NASA-TLX scale was applied,

where each participant was asked to identify the most important of the 15 pairwise dimension comparisons in relation to the task of viewing avatar images expressing different emotions.

Then, participants viewed the four images, during which EEG, GSR, and eye-tracking signals were recorded using an integrated signal device. Calibration was performed for each device beforehand. Each image was displayed for 6 s, with a 3-second rest period between images. An example of this procedure is shown in Figure 6. Lighting and temperature conditions were controlled (21°C).

The 6-second presentation per image is based on protocols established in the literature on visual emotion. For example, the International Affective Picture System (IAPS), a widely used normative database for affective and cognitive attention studies, typically presents images for ~6 s to allow affective responses to develop before subjective or physiological measurements. In EEG paradigms, although initial responses may occur on a millisecond scale, the integration of emotional and cognitive patterns usually requires presentations of several seconds to be reliably captured in frequency bands and power components (Costa et al. 2013). Similarly, GSR studies have reported peak variations several seconds after a stimulus, supporting the need for several-second durations in order to evaluate sustained

Table 2. Relationship between integrated devices, metrics, and their meaning.

Device	Metrics	Meaning
Ring	Emotional impact	Measures the number of specific changes and their intensity in the emotional state produced by a stimulus on a scale of 0% to 100%.
Diadem	Engagement	Measures the degree of involvement between the subject and the stimulus from 0% to 100%.
	Valence	Measures the degree of attraction to the stimulus. Valence can be positive or negative on a scale from 0% to 100%.
	Memorisation	Measures the intensity of cognitive processes in relation to stimuli on a scale from 0% to 100%.
	Workload	Measures the learner's concentration with respect to the stimulus on a scale from 0% to 100%.
Eye-tracking	Number of visits	A visit is considered when a participant makes a fixation inside the AOI with the previous one made outside of the AOI.
	Time visited	Time a participant spends looking at the AOI (regardless of whether they do so on one or more visits).
	Number of fixations during	How many times a participant makes different fixations in the AOI.



Figure 6. Image presentation procedure.

emotional responses (Francis and Oliver 2018). Finally, multimodal approaches combining EEG, GSR, and eye-tracking use stimulus durations in this range to ensure synchronisation and robustness of physiological measurements (López-Gil et al. 2016).

Once the viewing task was completed, the second part of the NASA-TLX was applied, in which participants rated each of the six dimensions.

4.4. Data analysis

Prior to testing the research questions, the normality of the sample distribution was evaluated. Skewness and

kurtosis values were analysed, considering absolute values below $|2.00|$ for skewness and $|8.00|$ for kurtosis as acceptable (Arias et al. 2013). Results showed a maximum skewness of 0.59 and a maximum kurtosis of 3.79, both within acceptable ranges. Consequently, the assumption of normality was considered to have been met, and parametric statistical tests were applied (Table 3).

A two-way factorial design with fixed effects (participant type and gender) was used. To address the research questions, two-way analysis of variance (ANOVA) was conducted. Effect sizes were calculated and interpreted following conventional criteria proposed by Cohen for

Table 3. Skewness and kurtosis analysis for NASA-TLX test results.

	N	Min	Max	M	SD	Skewness		Kurtosis	
						E	Standard error	E	Standard error
Mental demands	48	0.0	80	33.6	19.6	0.41	0.34	−0.36	0.67
Physical demands	48	0.0	70	26.0	18.7	0.59	0.34	−0.42	0.67
Effort	48	0.0	90	42.6	25.1	0.42	0.34	−0.50	0.67
Performance	48	20.0	100	77	14.8	−1.24	0.34	3.79	0.67
Frustration	48	0.0	100	42	30.1	0.15	0.34	−1.01	0.67
Overall score	48	0.0	100	57.3	28.6	−0.28	0.34	−0.95	0.67

Note: Min = Minimum; Max = Maximum; M = Mean; SD = Standard deviation.

partial eta squared (η^2p): small effect (≈ 0.01), medium effect (≈ 0.06), and large effect (≥ 0.14).

An exploratory and descriptive quantitative analysis was also conducted to complement the inferential analyses and facilitate interpretation of observed patterns. Orange Data Mining software (Demšar et al. 2013) was used for exploratory data visualisation. Specifically, box plots, scatter plots, heatmaps, and profile plots were used to examine the distribution of biomarkers and general trends according to participant type and gender. These visualisations were interpreted solely for exploratory and descriptive purposes, without statistical inferences; confirmatory conclusions were based solely on the ANOVA results.

Statistical tests were conducted using the IBM SPSS Statistics package (IBM Corp. 2025).

5. Results

The results corresponding to the two research questions are presented below:

RQ1. Are there significant differences in relevant AOIs (facial triangle region) in relation to physiological

indicators – Engagement, Impact, Memorization, Valence, Workload, number of visits, and visit duration – according to participant type (final-year university students, novice university lecturers, and experienced university lecturers), the emotion expressed by the avatar (positive or negative), and participant gender?

RQ2. Are there significant differences in non-relevant AOIs (outside the facial triangle) in relation to the same physiological indicators, according to participant type, the emotion expressed by the avatar, and participant gender?

Significant differences were identified in the number of visits to non-relevant AOIs when viewing the surprise image. More specifically, there were differences between Group 1 (university students) and Group 2 (novice university lecturers) ($\text{Diff} = 2.10$, $p = 0.05$), as well as between Group 1 and Group 3 (experienced university lecturers) ($\text{Diff} = 2.23$, $p = 0.01$). Notably, Group 3 did not register any visits to non-relevant AOIs, suggesting a more focused attention pattern on relevant areas of the stimulus (see Table 4).

To complement the inferential results and facilitate interpretation of the observed patterns, Figure 7 presents an exploratory scatter plot. This graph depicts

Table 4. Results of the fixed-effects one-way ANOVA for Image 1 (surprise), according to participant type (final-year university students, novice university lecturers, and experienced university lecturers).

	Group 1 M(SD) n = 22	Group 2 M(SD) n = 16	Group 3 M(SD) n = 10	Image 1 (surprise)			
				F	df	p	η_p^2
Engagement R	40.34(19.35)	39.80(16.37)	38.32(22.18)	0.04	2	0.96	0.00
Engagement NR	0.89(4.1)	2.32(7.10)	0(0)	0.74	2	0.48	0.03
Impact R	100(0)	100(0)	100(0)	–	2	–	–
Impact NR	4.5(21.3)	12.5(34.2)	0(0)	0.90	2	0.41	0.04
Memorisation R	22.6(8.9)	27.8 (14.9)	24.9(11.6)	0.89	2	0.42	0.04
Memorisation NR	0.7(3.3)	5(14.2)	0(0)	1.53	2	0.23	0.06
Valence R	1.1(20.4)	−1.3(54.1)	0.4(57.5)	0.01	2	0.99	0.00
Valence NR	0.9(4.3)	−0.4(4.1)	0(0)	0.64	2	0.53	0.03
Workload R	32.9(14.6)	24.1(17.4)	27.1(14.6)	1.54	2	0.23	0.06
Workload NR	1.6(7.5)	0.6(2.5)	1.3(4.3)	0.14	2	0.87	0.01
Number of visits R	1.3(1.1)	1.1(1.1)	1.5(1.5)	0.63	2	0.63	0.02
Number of visits NR	2.2(2.8)	0.1(0.3)	0(0)	0.46	2	0.00*	0.25
Time visited R	3.5(2.4)	3.1(2.6)	2.1(1.9)	1.19	2	0.31	0.05
Time visited NR	0.01(0.03)	0.02(0.05)	0(0)	0.85	2	0.43	0.04

* $p < 0.05$. Note: Group 1 = final-year university students; Group 2 = novice university lecturers with less than 4 years of professional experience; Group 3 = experienced university lecturers with more than 9 years of professional experience; R = relevant AOIs; NR = non-relevant AOIs; M = Mean; SD = Standard Deviation.

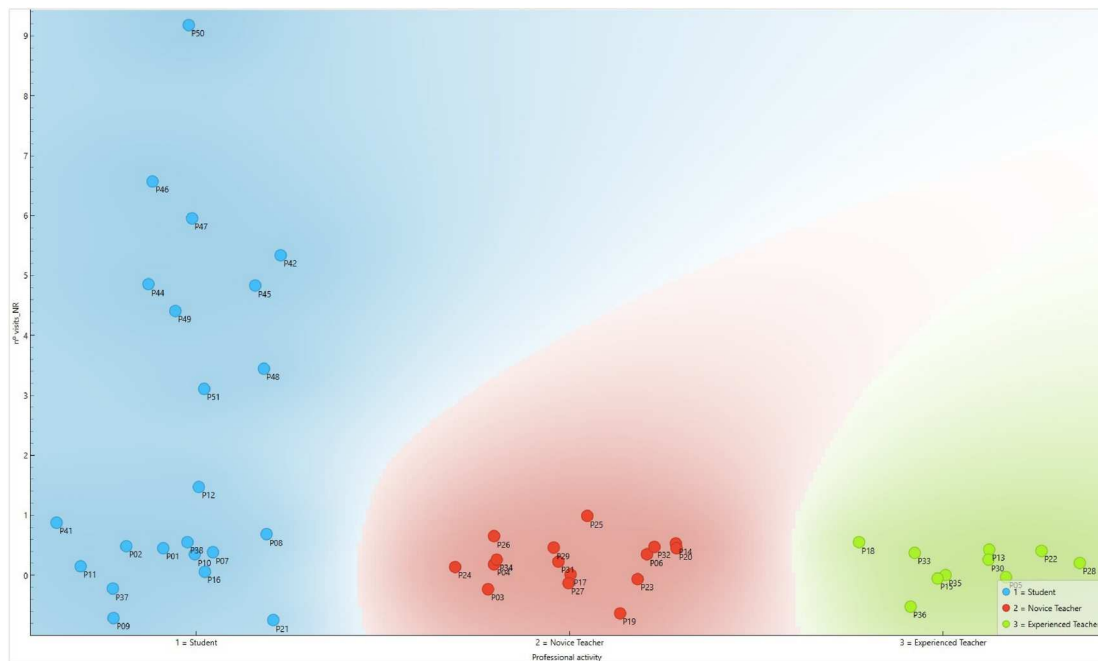


Figure 7. Scatter plot corresponding to Image 1 (surprise), showing the distribution of the physiological indicator number of visits in the non-relevant areas of interest (NR), where statistically significant differences were identified between the analysed groups.

the relationships between pairs of continuous physiological indicators derived from EEG, GSR, and eye-tracking, incorporating professional category and gender as visual grouping factors using colours and symbols. The visualisation allows identification of general trends and potential clustering among the different groups, without inferential purposes, complementing the conducted statistical analyses. In this context, a greater dispersion of values was observed in the student group, suggesting higher heterogeneity in their response patterns.

Statistically significant differences were also seen in time visited in the relevant areas of interest (R) while viewing Image 2 (joy), specifically between Group 2 (novice university lecturers) and Group 3 (experienced university lecturers), with shorter time visited in the latter group ($Dif = 1.6$, $p = 0.04$) (see Table 5). To complement these inferential results, Figure 8 presents an exploratory scatter plot corresponding to time visited in the relevant AOIs while viewing Image 2 (joy).

Table 5. Results of the one-way ANOVA for Image 2 (joy), according to participant type (final-year university students, novice university lecturers, and experienced university lecturers).

	Group 1 M(SD) n = 22	Group 2 M(SD) n = 16	Group 3 M(SD) n = 10	Image 2 (Joy)			
				F	df	p	η_p^2
Engagement R	42.8(15.7)	44.4(16.29)	38.48(19.92)	0.39	2	0.68	0.02
Engagement NR	3.24(10.5)	1.7(6.8)	1.4(4.5)	0.23	2	0.79	0.01
Impact R	95.5(21.3)	100(0)	80(42.1)	2.27	2	0.11	0.09
Impact NR	9.1(29.4)	6.3(25)	10(31.6)	0.07	2	0.93	0.00
Memorisation R	25.2(13.2)	20.1 (15.9)	19.3(13.1)	0.86	2	0.43	0.04
Memorisation NR	2.5(8.2)	0.72(2.9)	13.8(43.6)	1.42	2	0.25	0.06
Valence R	56.2(56.5)	59.5(58.7)	68.6(48.7)	0.17	2	0.84	0.01
Valence NR	5.1(17.7)	0(0)	8.5(27.01)	0.83	2	0.44	0.04
Workload R	27.3(14.4)	20.3(12.2)	24.5(18.6)	1.06	2	0.36	0.04
Workload NR	4.3(15.2)	0.2(0.6)	1.3(4.3)	0.63	2	0.54	0.03
Number of visits R	1.6(0.8)	1.9(0.9)	1.4(0.8)	1.02	2	0.37	0.04
Number of visits NR	0.2(0.5)	0.1(0.3)	0(0)	0.44	2	0.65	0.02
Time visited R	4.8(1.7)	5.2(0.8)	3.6(2.1)	3.46	2	0.04*	0.13
Time visited NR	0.1(0.2)	0.002(0.008)	0.02(0.07)	1.28	2	0.29	0.05

* $p < 0.05$. Note: Group 1 = final-year university students; Group 2 = novice university lecturers with less than 4 years of professional experience; Group 3 = experienced university lecturers with more than 9 years of professional experience; R = relevant AOIs; NR = non-relevant AOIs; M = Mean; SD = Standard Deviation.

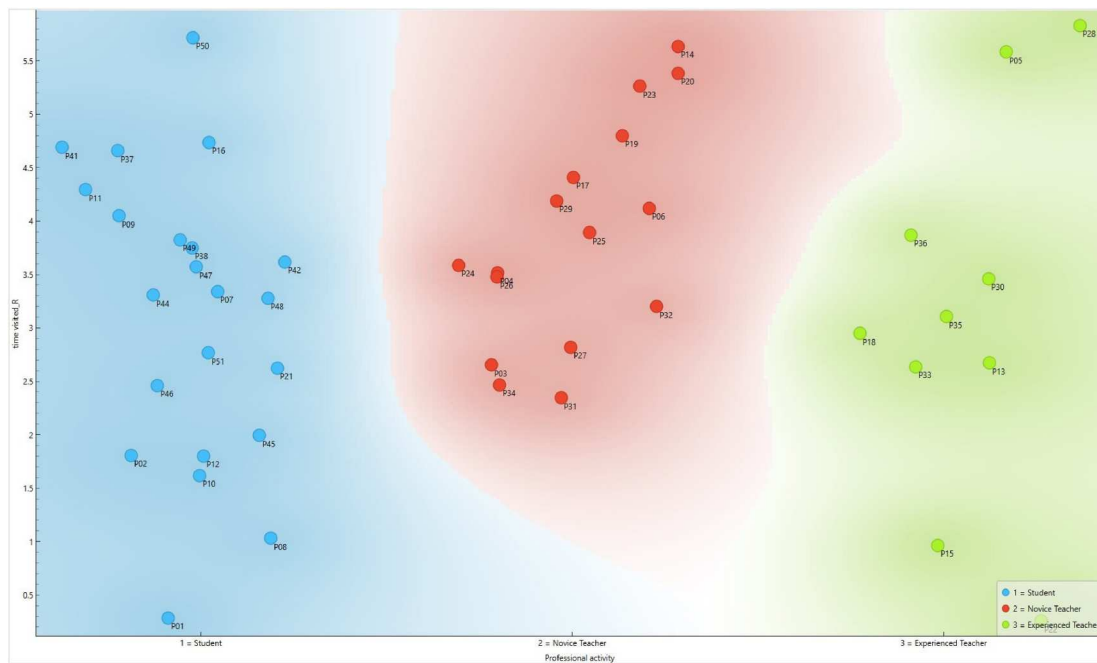


Figure 8. Scatter plot corresponding to Image 2 (Joy), showing the distribution of the physiological indicator number of visits in the relevant areas of interest (R), where statistically significant differences were identified between the analysed groups.

Table 6. Results of the one-way ANOVA for Image 3 (sadness), according to participant type (final-year university students, novice university lecturers, and experienced university lecturers).

	Group 1 M(SD) n = 22	Group 2 M(SD) n = 16	Group 3 M(SD) n = 10	Image 3 (Sadness)			
				F	df	p	η_p^2
Engagement R	35.1(19.9)	39.2(16.5)	38.8(22.1)	0.24	2	0.78	0.01
Engagement NR	6.4(15.5)	0(0)	0(0)	2.09	2	0.14	0.09
Impact R	95.5(21.3)	100(0)	88.9(33.3)	0.85	2	0.43	0.04
Impact NR	18.2(39.5)	0(0)	0(0)	2.60	2	0.09	0.11
Memorisation R	29.5(20.6)	25.4 (16.1)	18.9(11.4)	1.17	2	0.32	0.05
Memorisation NR	6.4(22.1)	0(0)	0(0)	1.03	2	0.37	0.04
Valence R	-69.44(46.7)	-68.01(43.9)	-81.9(44.7)	0.31	2	0.74	0.01
Valence NR	-7.8(25.8)	0(0)	0(0)	1.12	2	0.34	0.05
Workload R	21.3(10.8)	25.6(15.8)	21.4(22.4)	0.41	2	0.66	0.02
Workload NR	3.9(14.8)	0(0)	0(0)	0.89	2	0.42	0.04
Number of visits R	1.5(0.9)	1.5(0.8)	1.1(0.6)	0.80	2	0.46	0.03
Number of visits NR	0.2(0.4)	0.1(0.3)	0(0)	2.60	2	0.09	0.11
Time visited R	4.8(1.7)	0(0)	0(0)	1.70	2	0.20	0.07
Time visited NR	0.05(0.1)	0(0)	0(0)	2.18	2	0.12	0.09

* $p < 0.05$. Note: Group 1 = final-year university students; Group 2 = novice university lecturers with less than 4 years of professional experience; Group 3 = experienced university lecturers with more than 9 years of professional experience; R = relevant AOIs; NR = non-relevant AOIs; M = Mean; SD = Standard Deviation.

In contrast, no statistically significant differences were found in either the relevant (R) or non-relevant (NR) areas of interest according to participant group (final-year university students, novice university lecturers, and experienced university lecturers) when viewing Images 3 (sadness) or 4 (fear) (see Tables 6 and 7).

Looking at the gender variable, no statistically significant differences were found for Image 1 (surprise) (see Table 8). Statistically significant differences were observed for the valence indicator in relevant AOIs while viewing

Image 2 (joy), with a higher mean for women and a large effect size ($\eta_p^2 = 0.14$) (see Table 9). Similarly, there were significant differences in the workload indicator in relevant AOIs for the same image, also with a large effect size ($\eta_p^2 = 0.21$), with a higher mean in Group 1 (female) in both cases. Figures 9 and 10 show the distribution of participants in both groups with respect to the valence and workload indicators in relevant AOIs.

For Image 3 (sadness), statistically significant differences were found in the *Memorization* ($F = 5.53$, $p =$

Table 7. Results of the one-way ANOVA for Image 4 (fear), according to participant type (final-year university students, novice university lecturers, and experienced university lecturers).

	Group 1 M(SD) n = 22	Group 2 M(SD) n = 16	Group 3 M(SD) n = 10	Image 4 (Fear)			
				F	df	p	η_p^2
Engagement R	42.8(15.7)	44.4(16.29)	38.48(19.92)	0.91	2	0.41	0.04
Engagement NR	3.24(10.5)	1.7(6.8)	1.4(4.5)	0.08	2	0.92	0.00
Impact R	95.5(21.3)	100(0)	80(42.1)	0.81	2	0.45	0.03
Impact NR	9.1(29.4)	6.3(25)	10(31.6)	0.97	2	0.39	0.04
Memorisation R	25.2(13.2)	20.1 (15.9)	19.3(13.1)	0.34	2	0.71	0.01
Memorisation NR	2.5(8.2)	0.72(2.9)	13.8(43.6)	0.49	2	0.62	0.02
Valence R	56.2(56.5)	59.5(58.7)	68.6(48.7)	0.21	2	0.81	0.01
Valence NR	5.1(17.7)	0(0)	8.5(27.01)	0.72	2	0.49	0.03
Workload R	27.3(14.4)	20.3(12.2)	24.5(18.6)	1.46	2	0.24	0.06
Workload NR	4.3(15.2)	0.2(0.6)	1.3(4.3)	0.27	2	0.77	0.01
Number of visits R	1.6(0.8)	1.9(0.9)	1.4(0.8)	0.40	2	0.67	0.02
Number of visits NR	0.2(0.5)	0.1(0.3)	0(0)	0.30	2	0.74	0.01
Time visited R	4.8(1.7)	5.2(0.8)	3.6(2.1)	1.90	2	0.16	0.08
Time visited NR	0.1(0.2)	0.002(0.008)	0.02(0.07)	2.14	2	0.13	0.09

* $p < 0.05$. Note: Group 1 = final-year university students; Group 2 = novice university lecturers with less than 4 years of professional experience; Group 3 = experienced university lecturers with more than 9 years of professional experience; R = relevant AOIs; NR = non-relevant AOIs; M = Mean; SD = Standard Deviation.

Table 8. Results of the one-way ANOVA for Image 1 (surprise), according to gender (female vs. male).

	Group 1 Female M(SD) n = 29	Group 2 Male M(SD) n = 19	Image 1 (surprise)			
			F	df	p	η_p^2
Engagement R	38.8(11.8)	41.1(26.2)	0.19	1	0.67	0.00
Engagement NR	0.68(3.7)	1.9(6.5)	0.76	1	0.39	0.02
Impact R	100(0)	100(0)	–	1	–	–
Impact NR	6.9(25.8)	5.3(22.9)	0.05	1	0.82	0.00
Memorisation R	27.3(13.3)	21.1 (7.7)	3.36	1	0.07	0.07
Memorisation NR	0.5(2.9)	4.2(13.1)	2.16	1	0.15	0.04
Valence R	–3.8(44.6)	6.3(37.6)	0.67	1	0.42	0.01
Valence NR	0.7(3.7)	–0.4(3.7)	0.94	1	0.34	0.02
Workload R	31.1(13.1)	25.3(19.1)	1.55	1	0.22	0.03
Workload NR	1.6(6.7)	0.67(3.1)	0.26	1	0.61	0.01
Number of visits R	1.5(1.3)	0.9(0.9)	3.47	1	0.07	0.07
Number of visits NR	0.8(1.8)	1.5(2.6)	1.45	1	0.23	0.03
Time visited R	3(2.2)	3.1(2.6)	0.03	1	0.87	0.00
Time visited NR	0.0004(0.02)	0.01(0.04)	0.98	1	0.33	0.02

* $p < 0.05$. Note: R = relevant AOIs; NR = non-relevant AOIs; M = Mean; SD = Standard Deviation.

Table 9. Results of the one-way ANOVA for Image 2 (joy), according to gender (female vs. male).

	Group 1 Female M(SD) n = 29	Group 2 Male M(SD) n = 19	Image 2 (Joy)			
			F	df	p	η_p^2
Engagement R	43.5(9.2)	40.7(24.2)	0.96	1	0.33	0.02
Engagement NR	2.1(7.8)	2.7(9.1)	0.19	1	0.66	0.00
Impact R	96.5(18.6)	89.5(31.5)	1.57	1	0.22	0.03
Impact NR	6.9(25.8)	10.5(31.5)	1.44	1	0.24	0.03
Memorisation R	24.3(13.2)	19.1 (15.3)	0.10	1	0.75	0.00
Memorisation NR	1.4(5.8)	8.7(13.9)	0.52	1	0.47	0.01
Valence R	61.9(60.5)	56.8(46.2)	7.69	1	0.01*	0.14
Valence NR	2.7(14.3)	6.3(20.7)	1.66	1	0.20	0.03
Workload R	28.8(15.4)	17.6(10.7)	12.53	1	0.00*	0.21
Workload NR	28.8(15.4)	17.6(10.7)	0.22	1	0.64	0.00
Number of visits R	1.9(0.9)	1.6(0.6)	0.92	1	0.34	0.02
Number of visits NR	0.1(0.4)	0.2(0.4)	1.47	1	0.23	0.03
Time visited R	4.9(1.2)	4.4(2.2)	0.96	1	0.33	0.02
Time visited NR	0.02(0.09)	0.06(0.2)	0.19	1	0.66	0.00

* $p < 0.05$. Note: R = relevant AOIs; NR = non-relevant AOIs; M = Mean; SD = Standard Deviation.

0.02) and *Time visited* ($F = 4.39$, $p = 0.04$) indicators in relevant AOIs, with higher mean values in Group 1 (female). The distribution of participants by group for these indicators is shown in Figures 11 and 12 (Table 10).

Figure 11 shows the distribution of each participant in both groups.

For Image 4 (fear), statistically significant differences were found in the *impact* ($F = 7.11$, $p = 0.01$) and *valence* ($F = 5.30$, $p = 0.03$) indicators in non-relevant AOIs, with higher mean values in Group 1 (female) (see Table 11). The distribution of participants by group for these indicators is shown in Figures 13 and 14.

6. Discussion

Statistically significant differences between the student group and the two teacher groups were identified in the number of visits to non-relevant areas of interest (AOIs) while viewing the surprise image. The students' higher frequency of visits to non-relevant AOIs suggests elevated extraneous cognitive load, associated with irrelevant information that distracts from the task objective, whereas the lecturers demonstrated more focused processing with lower extraneous load. In the scatter plot, students exhibit greater dispersion, supporting the interpretation of less efficient working memory use than lecturers members. This indicates that the avatar representing surprise may not be effective as a pedagogical agent for students, as it does not adequately focus attention.

When viewing the joy image, novice university lecturers exhibited longer time visited in relevant AOIs

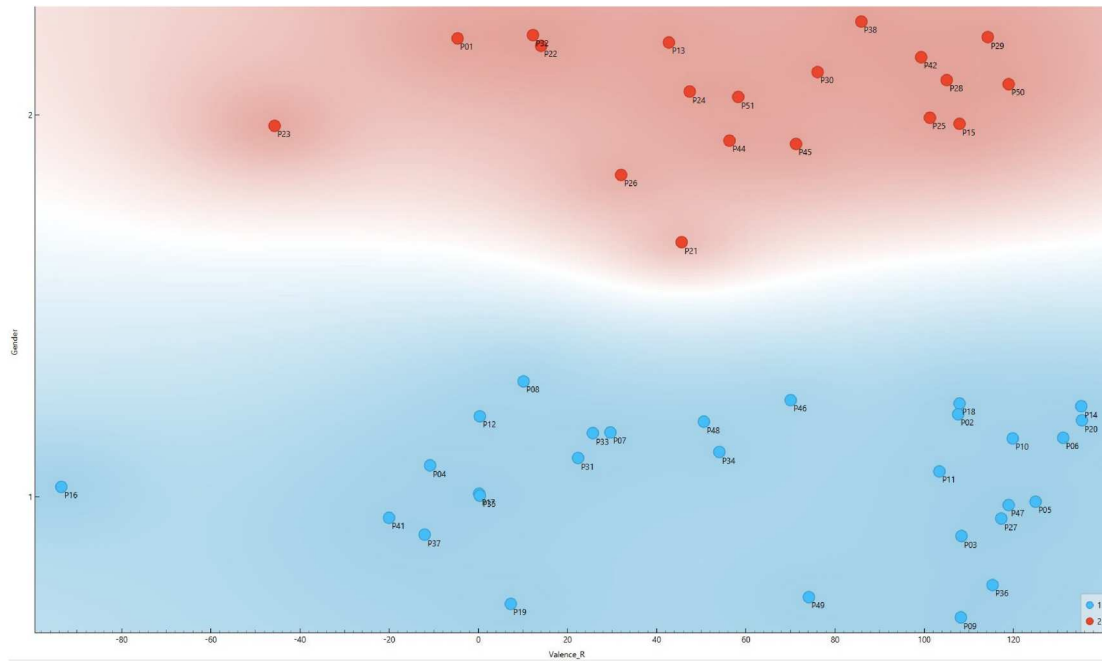


Figure 9. Scatter Plot for Image 2 (joy), showing the distribution of the physiological indicator valence in relevant AOs, where statistically significant differences between the groups were observed. Note: Group 1 = female; Group 2 = male.

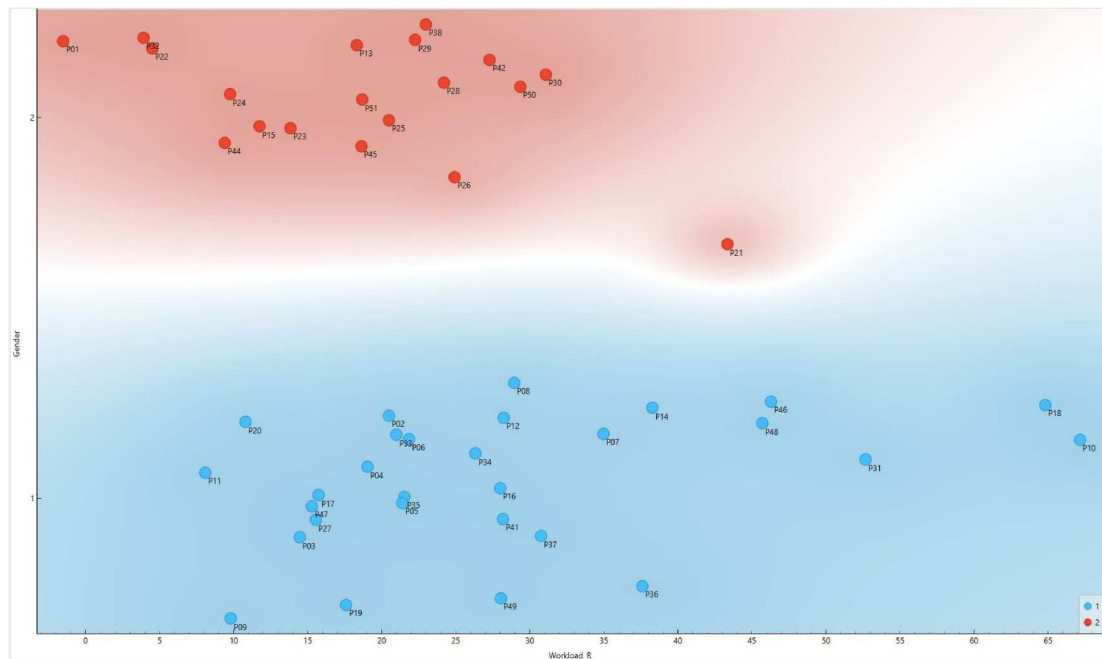


Figure 10. Scatter Plot for Image 2 (joy), showing the distribution of the physiological indicator workload in relevant AOs, where statistically significant differences between the groups were observed. Note: Group 1 = female; Group 2 = male.

and more homogeneous behaviour, suggesting higher germane cognitive load, as these participants actively integrated the avatar's information with prior knowledge, optimising mental schema construction. In contrast, no differences were detected for the sadness or fear images, indicating that these emotions did not

generate notable variations in intrinsic cognitive load associated with task complexity.

Looking at gender, the higher mean values in valence and workload indicators from women compared to men, particularly for the joy image, may reflect an increase in both germane load – due to effort devoted

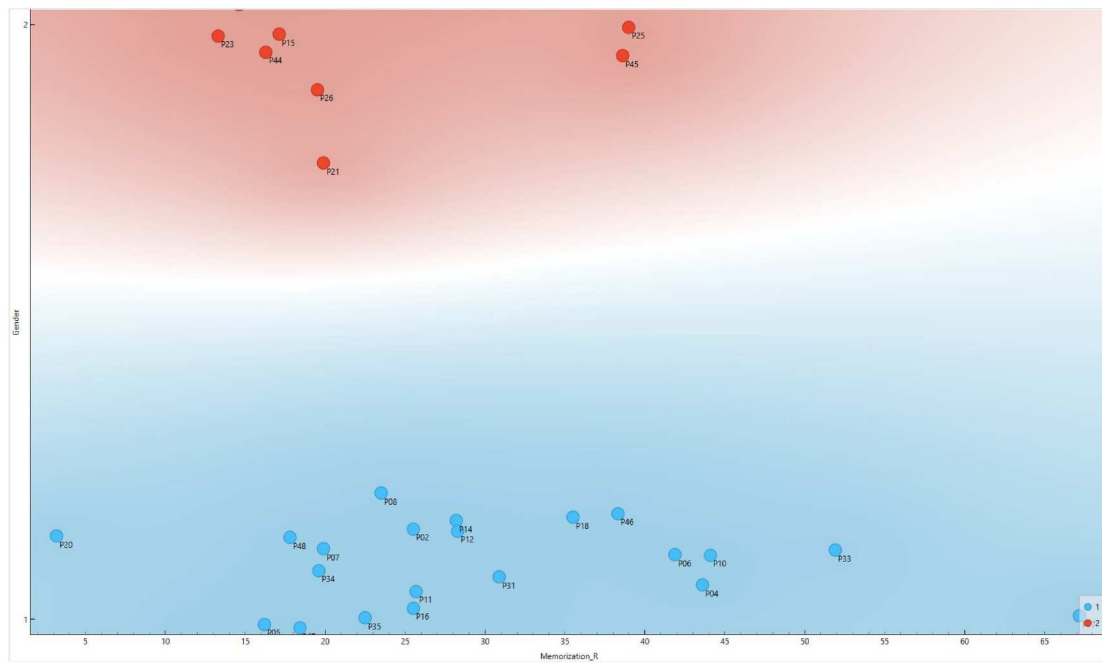


Figure 11. Scatter Plot for Image 3 (sadness), showing the distribution of the physiological indicator *memorization* in relevant AOIs, where statistically significant differences between the analysed groups were identified.

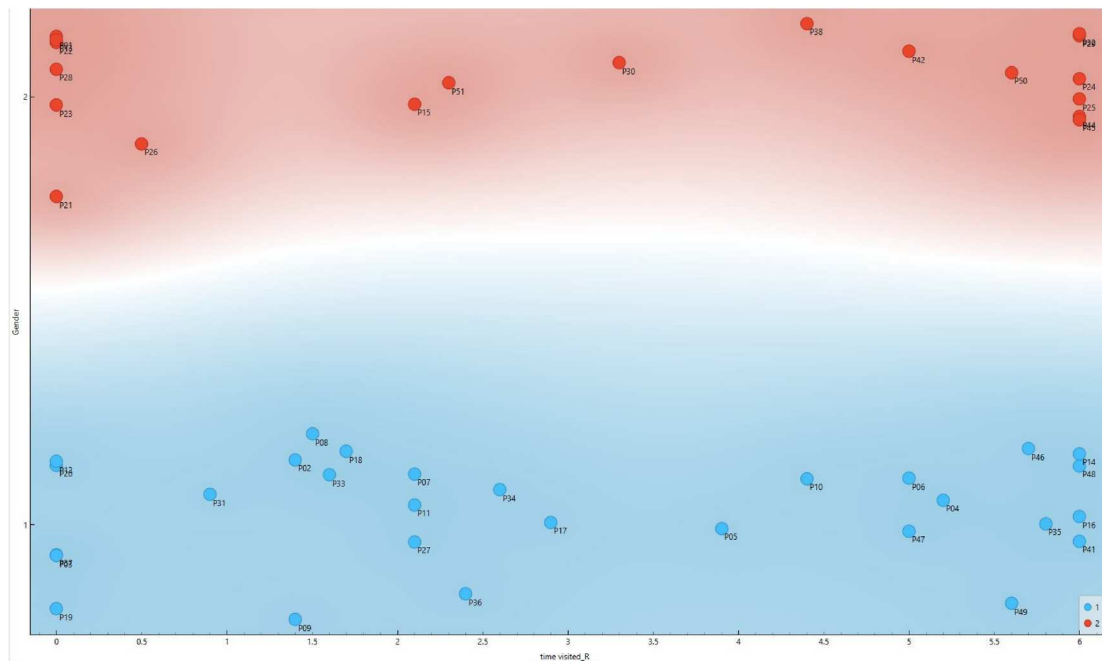


Figure 12. Scatter Plot for Image 3 (sadness), showing the distribution of the physiological indicator *Time visited R* in relevant AOIs, where statistically significant differences between the analysed groups were identified.

to integrating emotional information – and intrinsic load, if the emotion adds processing complexity. Similarly, greater memorisation and longer time visited in response to the sadness image among women indicate deeper processing of negative information, suggesting differences in cognitive and emotional integration

(Bao et al. 2019; Bilalpur et al. 2020; Dubovi 2022; Kumar 2024; Yu et al. 2024).

The main objective of this study was to illustrate how the use of integrated multichannel devices (eye tracking, GSR, EEG) enables identification of physiological indicators associated with viewing positive and

Table 10. Results of the one-way ANOVA for Image 3 (sadness), according to gender (female vs. male).

	Group 1 Female M(SD) n = 29	Group 2 Male M(SD) n = 19	Image 3 (Sadness)			
			F	df	p	η_p^2
Engagement R	39.9(16.8)	32.7(21.7)	1.66	1	0.20	0.04
Engagement NR	4.9(13.7)	0(0)	2.24	1	0.14	0.05
Impact R	100(0)	88.9(32.3)	3.47	1	0.07	0.07
Impact NR	13.8(35.1)	0(0)	2.76	1	0.10	0.06
Memorisation R	30.7(13.2)	18.2(14.8)	5.53	1	0.02*	0.11
Memorisation NR	4.9(19.4)	0(0)	1.12	1	0.29	0.02
Valence R	−79.6(43.7)	−57.64(44.1)	2.85	1	0.10	0.06
Valence NR	−5.9(22.6)	0(0)	1.22	1	0.28	0.03
Workload R	25.8(13.9)	17.9(15.88)	3.12	1	0.08	0.06
Workload NR	3.02(12.9)	0(0)	0.98	1	0.33	0.02
Number of visits R	1.5(0.8)	1.3(0.9)	0.93	1	0.34	0.02
Number of visits NR	0.1(0.3)	0.06(0.2)	0.32	1	0.58	0.01
Time visited R	5.02(1.6)	3.9(2.1)	4.39	1	0.04*	0.09
Time visited NR	0.022(0.08)	0.02(0.1)	0.00	1	0.99	0.00

* $p < 0.05$. Note: R = relevant AOs; NR = non-relevant AOs; M = Mean; SD = Standard Deviation.

negative avatar emotions across different university groups (students and both novice university lecturers and experienced university lecturers), considering working memory limits (15–30 s) and standardised presentation times (6 s per image, 3 s rest intervals). The results show that professional experience and gender modulate the distribution of cognitive load, guiding avatar design to maximise germane load, minimise extraneous load, and adjust intrinsic load according to task complexity.

Overall, these findings highlight that the design of avatars as pedagogical agents must consider both group characteristics and gender, integrating strategies that optimise attention, cognitive effort, and student motivation through appropriate management of the three types of cognitive load (Almukhtar et al. 2025; Chandler and Sweller 1991; Dubovi 2022; Van Merriënboer and Sweller 2010).

7. Conclusions

In summary, affective computing technology represents both a challenge and an opportunity for the development of multimedia prototypes (Almukhtar et al. 2025; Picard et al. 2004; Sáiz-Manzanares et al. 2024a). Using integrated multichannel devices provides valuable information regarding engagement and cognitive load indicators derived from unconscious responses (Saavedra et al. 2025). Furthermore, visualisation techniques applied to multichannel analyses make it easier to compare where each participant's result sits in relation to the others (Sáiz-Manzanares et al. 2025). Collectively, this constitutes progress in human-machine interaction (Saavedra et al. 2025) and will contribute to optimising

pedagogical resources (Xue, Wang, and Qiu 2025; Yu, Androsof, and Yan 2025). Emotional responses appear to vary according to educational role (Bailen, Green, and Thompson 2019) and gender (Bao et al. 2019; Bilalpur et al. 2020).

It is therefore important to emphasise the need to examine behaviours in diverse samples and to analyse relationships between underlying emotional and cognitive constructs in order to interpret findings appropriately in multimedia educational contexts (Ba and Hu 2023; Schillinger et al. 2021). Using integrated signal devices provides more reliable evidence of material processing (Ba and Hu 2023; Dubovi 2022) than users' subjective perceptions alone.

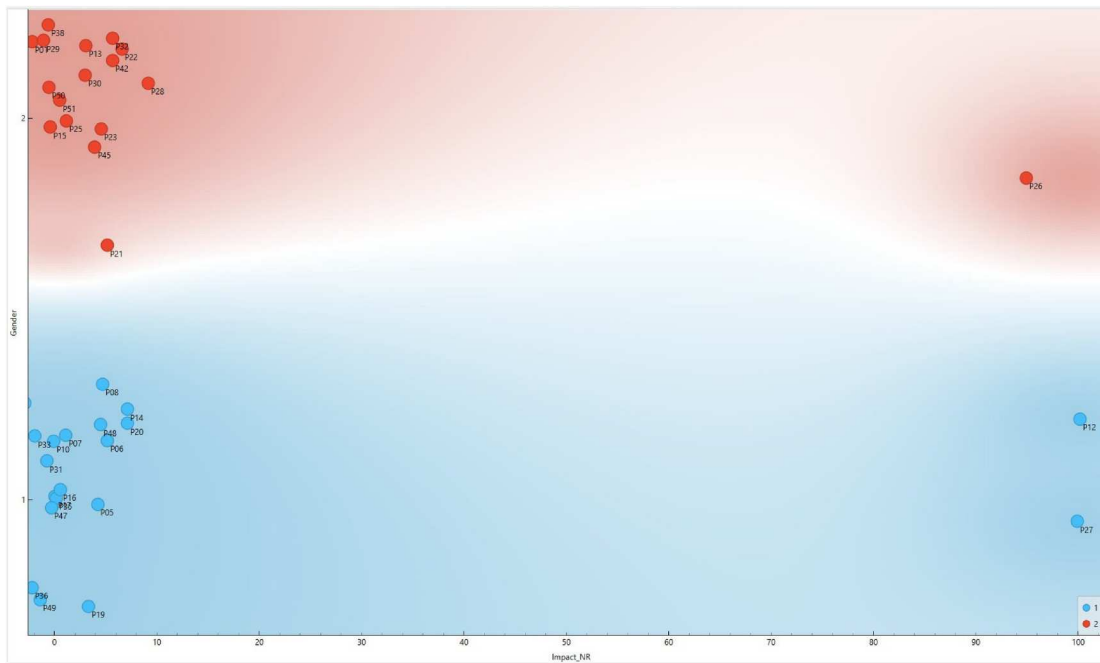
Despite its limitations, this study contributes an analysis of physiological responses through multi-channel devices (eye tracking, GSR and EEG) applied to the design of an avatar as a pedagogical agent in higher education, considering differences according to participant group (final-year university students or lecturers) and gender. The findings may support adjustment of avatar design according to teacher profile (final-year university students vs. experienced university lecturers) and gender, contributing to personalised learning. Although research of this type remains limited, the literature advocates its expansion (Ding, Ma, and Li 2025).

In summary, empirical evidence indicates that integrating cognitive load and emotions is key to optimising student attention, motivation and performance in technological environments. Minimising extraneous load and fostering germane load, through combining educational avatars with physiological signals (eye tracking, GSR, EEG), facilitates personalised learning by leveraging positive emotions and mitigating the effects of

Table 11. Results of the one-way ANOVA for Image 4 (fear), according to gender (female vs. male).

	Group 1	Group 2	Image 4 (Fear)			
	Female M(SD) n = 29	Male M(SD) n = 19	F	df	p	η_p^2
Engagement R	38.2(16.9)	35.9(20.1)	0.01	1	0.91	0.00
Engagement NR	14.01(22.9)	13.1(30.2)	3.27	1	0.08	0.07
Impact R	100(0)	89.5(31.5)	0.01	1	0.94	0.00
Impact NR	37.9(49.4)	36.8(49.6)	7.11	1	0.01*	0.13
Memorisation R	26.5(15.02)	15.3(12.7)	0.07	1	0.80	0.00
Memorisation NR	11.6(19.8)	10.2(16.9)	0.86	1	0.36	0.02
Valence R	−49.2(54.4)	−35.7(40.5)	0.49	1	0.49	0.01
Valence NR	−19.7(42.4)	−11.9(28.9)	5.30	1	0.03*	0.10
Workload R	26.3(13.6)	17.2(13.3)	0.41	1	0.53	0.01
Workload NR	6.7(14.3)	9.9(21.4)	1.45	1	0.23	0.03
Number of visits R	2.9(1.5)	2.4(1.5)	0.11	1	0.75	0.00
Number of visits NR	0.4(0.6)	0.5(0.6)	0.48	1	0.49	0.01
Time visited R	3.4(1.3)	3.1(1.6)	0.06	1	0.80	0.00
Time visited NR	0.4(0.8)	0.5(0.9)	0.01	1	0.91	0.00

* $p < 0.05$. Note: R = relevant AOs; NR = non-relevant AOs; M = Mean; SD = Standard Deviation.

**Figure 13.** Scatter Plot for Image 4 (fear), showing the distribution of the physiological indicator *Impact* in non-relevant AOs, where statistically significant differences between the analysed groups were identified.

negative emotions on working memory and decision-making (Dubovi 2022). These multimodal strategies underscore the importance of adapting educational materials and platforms to users' cognitive and affective states, thereby maximising multimedia learning effectiveness (Picard et al. 2004; Saavedra et al. 2025). Finally, descriptive visual analyses, such as scatter plots, enable visualisation of each user's relative positioning in terms of the indicator studied, opening up a promising avenue for individualised analysis and personalised instructional design.

The limitations of the study and future research directions are outlined below.

7.1. Study limitations

This study has certain limitations affecting the generalisability of the findings, primarily related to the use of convenience sampling and the sample size ($n = 48$). Nevertheless, it is important to note that integrated signal studies require voluntary participation and informed commitment from users, which complicates

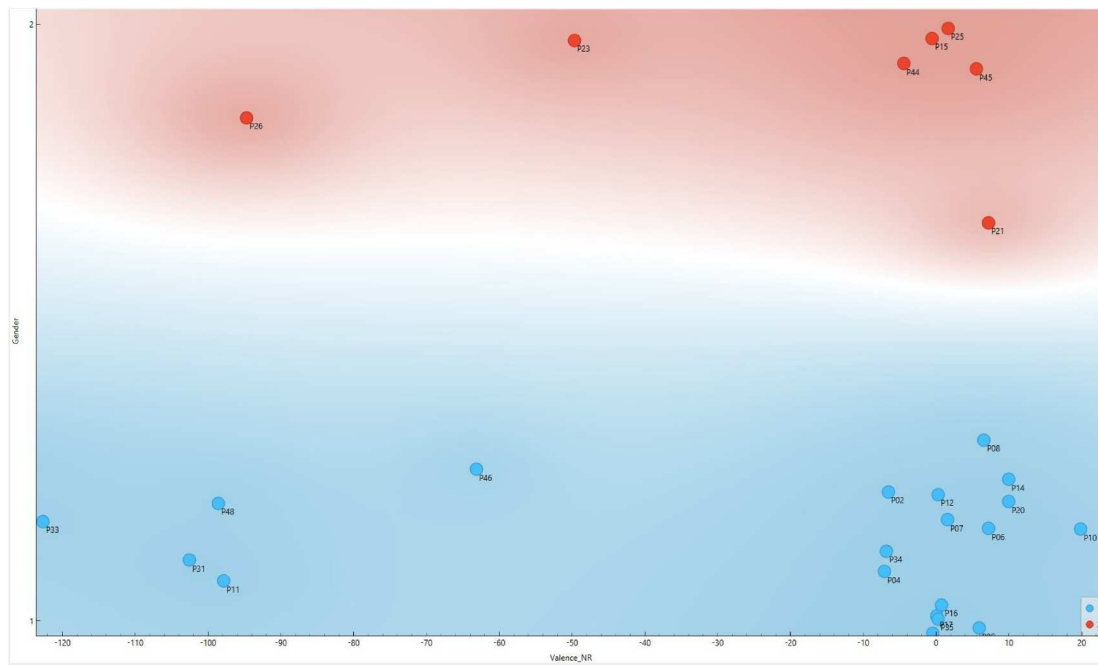


Figure 14. Scatter Plot for Image 4 (fear), showing the distribution of the physiological indicator *valence* in non-relevant AOs, where statistically significant differences between the analysed groups were identified.

randomisation and recruitment of large samples. Moreover, using integrated signal devices involves considerable time investment per participant, as well as specialised training in both device operation and metric interpretation.

Despite these limitations, rapid technological evolution suggests that in the medium term such procedures will become more accessible and indispensable tools in educational resource design. Key advantages include reducing prototype development errors and promoting more effective learning.

7.2. Future research directions

Further studies are required to improve our understanding of integrated signal analysis and its pedagogical implications (Ba and Hu 2023; Dubovi 2022). Although methodologically demanding, this approach allows a more comprehensive understanding of information processing (Almukhtar et al. 2025; Sáiz-Manzanares et al. 2024a) and is fundamental for the design of educational materials, particularly in technological environments (Ba and Hu 2023; Chandler and Sweller 1991; Liu et al. 2023). It also contributes to optimising pedagogical resources in virtual learning platforms (Xue, Wang, and Qiu 2025; Yu, Androsov, and Yan 2025) and facilitates identification of user differences according to individual characteristics (Bailen, Green, and Thompson 2019; Schillinger et al. 2021).

Future research could expand sample sizes, evaluate responses to additional pedagogical resources, and incorporate further variables such as age, in order to produce more robust findings and improve their applicability.

Author contributions

CRedit: **María Consuelo Sáiz-Manzanares:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Celia Toribio-Casado:** Investigation, Software, Writing – review & editing; **Gloria Pérez-López De-Echazarreta:** Investigation, Writing – review & editing; **Rocío Águeda Miguel:** Conceptualization, Investigation, Software, Writing – review & editing; **Irene González-Díez:** Investigation, Writing – review & editing; **Marina Muñoz-Arranz:** Investigation, Writing – review & editing; **Miguel Ángel Carbonero-Martín:** Investigation, Writing – review & editing; **Luis Jorge Martín-Antón:** Investigation, Methodology, Supervision, Writing – review & editing.

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Data availability statement

Data will be made available on request.

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