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Research Article/Education in Engineering

Study on the Effect of Integrated Augmented Reality on Student Performance and Attention Level Using Facial Feature Analysis

Estudio sobre el efecto de la realidad aumentada en el rendimiento y nivel de atención de los estudiantes mediante el análisis de rasgos faciales

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ABSTRACT

Augmented reality (AR) is an emerging technology that enhances interactive educational modules by helping students to visualize complex concepts, thereby improving engagement and academic performance. This study aimed to assess the effects of an AR-based educational module on students' cognitive engagement during online learning, specifically focusing on liver cancer cell characterization as an extension of the cell structure topics in the biology *syllabus*. A total of 104 students were divided into three groups: one using the AR module, another using a conventional module, and a control group. The students' performances were assessed through pre-test and post-test analyses. Additionally, the facial features of the AR group were analyzed using MediaPipe's Face Mesh algorithm to calculate the eye aspect ratio (EAR) which determines attention levels based on the opening and closure of the eyes. The results showed that the AR-based module had a positive effect on students' performance (9.73%) compared to the conventional module and effectively captured students' attention during the first half of the lesson. This integration of technology is beneficial for enhancing online teaching practices, particularly when it comes to engaging biomedical engineering students with challenging biology topics like cancer cell characterization.

Keywords: educational technology, student engagement, eye aspect ratio (EAR), biomedical engineering, online learning

RESUMEN

La realidad aumentada (AR) es una tecnología emergente que potencia los módulos educativos interactivos al ayudar a los estudiantes a visualizar conceptos complejos, mejorando el *engagement* y el rendimiento académico. Este estudio tuvo como objetivo evaluar los efectos de un módulo educativo basado en AR sobre el *engagement* cognitivo de los estudiantes durante el aprendizaje en línea, con un enfoque específico en la caracterización de células de cáncer de hígado como una extensión de los contenidos sobre estructura celular del *syllabus* de biología. Un total de 104 estudiantes se dividió en tres grupos: uno que utilizó el módulo de AR, otro que empleó un módulo convencional y un grupo de control. El desempeño de los estudiantes se evaluó mediante análisis de pre- y postests. Adicionalmente, se analizaron los rasgos faciales del grupo de AR utilizando el algoritmo Face Mesh de MediaPipe para calcular la relación de aspecto ocular (EAR), la cual permite determinar los niveles de atención a partir de la apertura y el cierre de los ojos. Los resultados mostraron que el módulo basado en AR tuvo un efecto positivo en el rendimiento de los estudiantes (9.73 %) en comparación con el módulo convencional y que captó eficazmente la atención de los estudiantes durante la primera mitad de la sesión. Esta integración tecnológica resulta beneficiosa para mejorar las prácticas de enseñanza en línea, especialmente para involucrar a estudiantes de ingeniería biomédica en temas complejos de biología como la caracterización de células cancerígenas.

Palabras clave: tecnología educativa, *engagement* estudiantil, relación de aspecto ocular (EAR), ingeniería biomédica, aprendizaje en línea

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Introduction

Online learning has been steadily growing for the past two decades. Thanks to advancements in technology and the increasing number people using the Internet for education around the world [1], long-distance education has become increasingly popular, especially in higher education settings [2]. However, one of the primary challenges of online learning is maintaining student engagement and focus throughout each session. A study by Rahmat and Tuzzahra [3] found that online learning in biology during the COVID-19 pandemic, which primarily emphasized low-level cognitive activities, could potentially cause cognitive distress in students, particularly those in the medium to high cognitive ability range.

To address this challenge, educators have begun incorporating technology into their teaching methods to enhance interactivity [4]. Augmented reality (AR) is one of the emerging technologies being utilized for the development of interactive educational modules, thanks to its ability to blend virtual components with real-world objects in order to visualize complex content making it easier for students to understand [5, 6]. While AR is widely known for enhancing learning experience, there is a need to rigorously assess students' level of cognitive engagement, with a particular focus on whether the novelty of AR leads to sustained attention and improved academic performance in unsupervised online settings.

Furthermore, assessing engagement in online environments requires effective methods since the use of biological or electrical sensors is limited and self-report surveys are prone to bias. This study seeks to address this gap by integrating computer vision, particularly using a facial landmark detection algorithm to assess student attention through the eye aspect ratio (EAR).

This study explored the potential of an AR-based educational module for enhancing students' cognitive engagement, specifically focusing on the characterization of liver cancer cells. Cognitive engagement was measured based on the students' performance and level of attention. A quasi-experimental research work was designed to address the following research questions:

1. Does the proposed AR-based educational module affect students' performance in comparison with standard conventional video-based modules?

2. Does the proposed AR-based educational module provide a learning alternative that can effectively capture students' attention?

We hypothesized that:

1. Students using the AR-based module would achieve significantly higher post-test accuracy scores than those using conventional modules.

2. The AR-based module would sustain attention levels (EAR>0.25) throughout the learning session.

This article is organized as follows. This introductory section further elaborates on background theory, definitions, and related works through a literature review. The methodology section outlines the techniques used in this research, including the development of conventional and AR-based modules, the tests employed to assess student performance, and the facial feature analysis conducted to measure attention. The results section presents our findings, while the discussion section provides a deeper analysis of the results. Finally, the conclusion section summarizes the overall findings of this research.

Literature review

Augmented reality in biomedical engineering and cancer visualization

AR is a technology that allows augmenting objects with a layer of information that is virtually hosted in real-time while retaining their functions and purposes [7]. Previous studies have suggested that using AR in learning yields better outcomes in terms of student motivation and academic performance when compared to conventional methods [8]. However, recent meta-analyses provide another complex perspective: a study on secondary biology education found that, while groups using AR show significantly higher attentiveness and participation, their post-test performance improvements are often statistically equivalent to those of the control [9]. This suggests that, rather than replacing the conventional method entirely, AR can potentially serve as a sort of 'cognitive hook' to maintain focus during complex lessons [10].

In biology lessons, particularly in the field of biomedical engineering, AR is widely used to explore the human body in depth, allowing students to observe organs in their actual size and shape. A systematic review of 40 empirical studies highlighted that cell biology and human anatomy are the dominant areas for AR applications, as this technology serves to bridge the gap between 2D textbook illustrations and conceptual understanding in 3D. Meanwhile, mobile AR has been identified as the most scalable medium for these interventions, given the widespread use of smartphones among students [9].

Furthermore, AR applications for oncology and tumor visualization are emerging. AR has been employed to visualize the characteristics of cells and various types of cancers, including breast cancer [11], prostate cancer [12], and brain tumors [13]. The goals of employing AR in studying cancer cells include detection, diagnosis, surgical guidance, and patient education. For example, the works by Weiß, et al. [12] and Shan, et al. [13] showed that AR systems can display the characteristics of cancer cells over physical markers, enhancing their understanding.

However, a gap remains in the microscopic characterization of cells for educational purposes. There is a lack of accessible mobile AR modules specifically designed to teach morphological differentiation in terms of size, nuclear shape, and chromatin dispersion between healthy and cancerous cells. This study aims to address this gap by adapting AR for mobile devices while providing an inexpensive and accessible learning experience regarding cell characterization. Nevertheless, further research is needed to examine the specific cognitive impacts of AR applications on students studying biology-related subjects [14].

Measuring cognitive engagement and attention

Cognitive engagement refers to the psychological state in which students are willing to exert effort to comprehend a subject or topic and to remain focused for an extended period of time [15]. Cognitive engagement can be assessed using various methods and tools, such as self-report scales, observations, teacher ratings, content analysis, and physiological sensors, among others. While self-report scales are often the most convenient method for classroom use [16], their results are susceptible to bias since the questionnaire may be completed by students or teachers.

Alternatively, researchers use students' achievement to determine the effect of AR on their ability to recall lessons, an indicator of cognitive engagement [17]. Pre- and post-assessments are designed to measure the differences in student performance before and after the implementation of AR-based educational modules [18, 19].

In addition, attention is among the cognitive processes associated with the effort exerted while performing tasks that require mental energy. Students demonstrate attentiveness or sustained attention when they can maintain their focus over a prolonged period of time. Previous studies have utilized physiological sensors to assess students' attention, *e.g.*, measuring brain waves [20] and body-tracking sensors for monitoring head pose, facial features, and body gestures as indicators of attention and engagement [21]. Ideally, the use of sensors is more beneficial in a physical classroom setting than in an online learning environment. To address this, data obtained via computer vision techniques are employed to measure attention when the use of sensors or devices is limited.

Computer vision is a crucial field of artificial intelligence that strives to allow computers to interpret visual information from images or videos, mimicking the visual perception capabilities of humans [22]. Through the integration of machine learning models and deep learning techniques, computer vision can classify images, detect objects, and perform semantic segmentation tasks. One application of computer vision is facial detection, which analyzes facial characteristics from images or videos [23]. The implementation of computer vision in measuring student engagement online was discussed in a review by Dewan, et al. [24]. This type of analysis has some advantages, including the use of the low-cost cameras available on mobile phones, tablets, or computers to capture images or videos of the students during the online learning session, with the purpose of assessing engagement.

The eye aspect ratio technique

Various parameters involved in facial feature detection, including facial expressions, emotions, head pose, eye movements, and mouth opening [25-27] can be utilized to measure engagement in terms of attention. Computer vision algorithms can detect specific facial landmarks, which can be used for further analysis in measuring student attention. For instance, Vignesh, et al. [28] utilized facial landmark point detection to estimate students' head pose during online classes and measure their attentiveness. Thiha and Rajasekera [29] used landmark detection in the eye area to determine face orientation, measuring the eye blink rate of video-conference attendees in order to study their engagement.

Furthermore, facial landmark points can be used to measure attention levels through EAR analysis. The EAR is a ratio of the eye region obtained from measuring the Euclidean distance between specific eye coordinates. It helps to determine a person's attentiveness by measuring the degree of openness and closeness of their eyes. When someone is intensely focused on a task such as reading or concentrating, they may involuntarily squint or narrow their eyes [30]. An EAR value ≥ 0.25 suggests attention [31], whereas values ≤ 0.20 indicate drowsiness and lack of attention [32]. This threshold for EAR values was recently validated in an artificial intelligence (AI) monitoring system [33]. Additionally, leveraging tools such as MediaPipe's Face Mesh offers a lightweight and non-invasive alternative to heavy sensor equipment. This study aligns with the current state-of-the-art methodologies for eye movement detection [34].

Methodology

Research Instrument

In this work, we developed an educational module to explore the characteristics of hepatic cancer cells, as an extension of the study of cell characteristics. The module discussed the differences between healthy liver cells (hepatocytes) and a common type of hepatic cancer cell: hepatocellular carcinoma (HCC). Two types of modules, conventional and AR-embedded, were developed and published to assess their effectiveness in increasing students' cognitive engagement.

The standard conventional module consisted of four sections: the anatomy of the human liver, the characteristics of hepatocytes and HCC, biopsy procedures for HCC detection, and the differences between hepatocytes and HCC as seen under microscopes. The module described the common characteristics of hepatocytes and HCC in terms of morphology, including the cell size and shape, the shape of the nuclei, and the cytoplasmic volume. Information on cell morphology was obtained from a previous study by Sawai, et al. [35]. For the standard conventional method of learning, the module was published in video format (.mkv) for online use. An excerpt from the educational module is shown in Fig. 1.

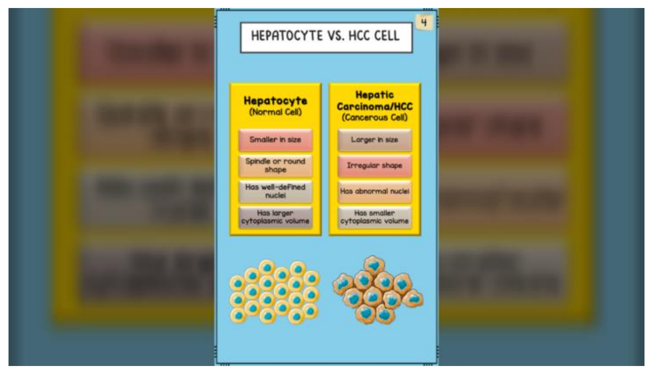

Figure 1. Example of a video snippet extracted from the educational module, explaining the difference between hepatocytes and HCC
Source: Authors

Subsequently, the educational module was transformed into its AR-based counterpart in the form of a mobile application. The AR-based module uses specific target images or markers that can be scanned using the application to reveal AR content. This content aligns with some chapters of the standard conventional module, covering human liver anatomy, the characteristics of healthy and cancerous liver cells, the liver biopsy process, and examples of stained and phase-contrast microscopic images of healthy and cancerous liver cells. These markers are images related to the module's contents, as displayed in Fig. 2.

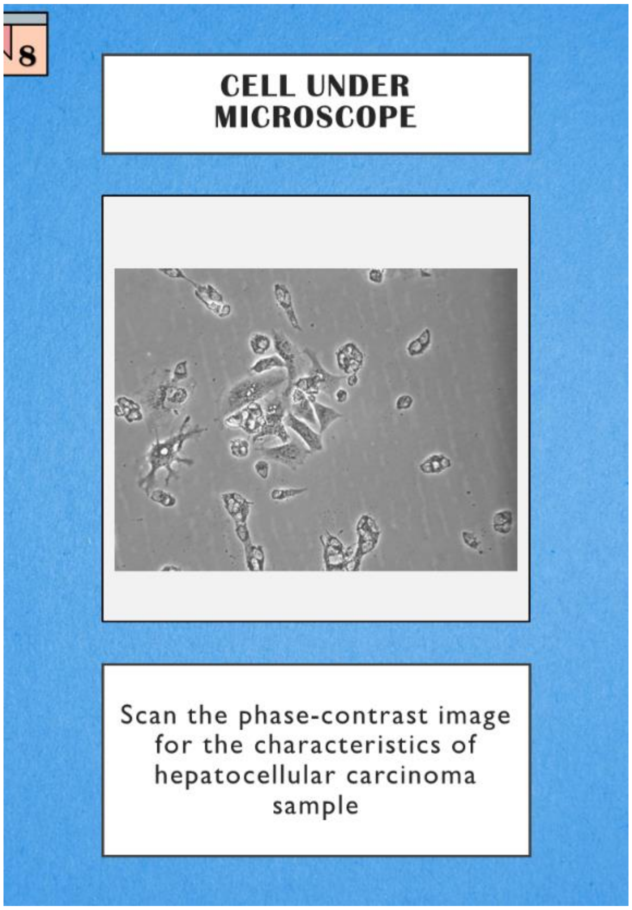

Figure 2. Example of a marker in the AR-based module
Source: Authors

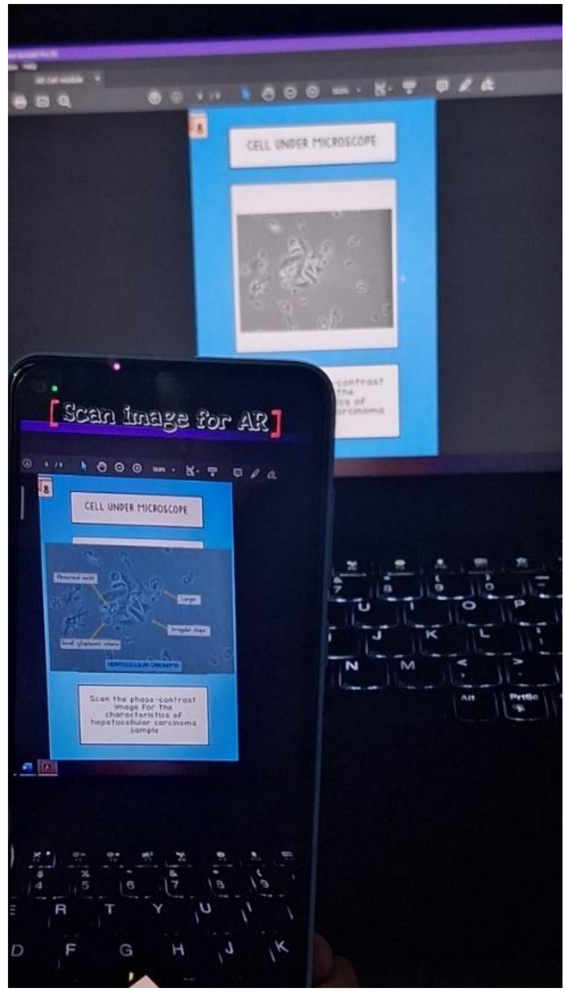

Figure 3. User scans a marker that triggers virtual information on the mobile device's screen
Source: Authors

The mobile AR application was developed using Unity and the EasyAR software development kit (SDK). The framework utilized was EasyAR Sense Unity Plugin Samples, which supports AR based on planar image targets or markers. This functionality allows users to scan the marker using their device's camera, projecting virtual information onto the screen overlaying the marker, as depicted in Fig. 3.

Test questions

Test questions based on the educational modules were designed to assess the performance of the students, who were presented with a series of microscopic images of healthy (hepatocytes) and cancerous (HCC) liver cells. They were then asked to correctly identify the images of the cancerous cells. The test consisted of eight questions, which were divided into two sections based on the observation method used. The first four questions (A, B, C, and D) were based on stained cell samples viewed under a light microscope, while the remaining questions (E, F, G, and H) were based on cell samples viewed under a phase contrast microscope.

Real samples were used in both educational modules and test questions to differentiate between healthy and cancerous liver cells by examining their structures. Well-differentiated cancerous liver cells have a finely granular eosinophilic cytoplasm, round nuclei with dispersed chromatin, and prominent nucleoli [36]. In contrast, a healthy liver cell has a granular cytoplasm, prominent nucleoli, and a round, centrally placed nucleus [37]. The stained cell sample was obtained from online resources, while the phase contrast sample was self-collected. Examples of the cell sample images used in the educational module are shown in Fig. 4.

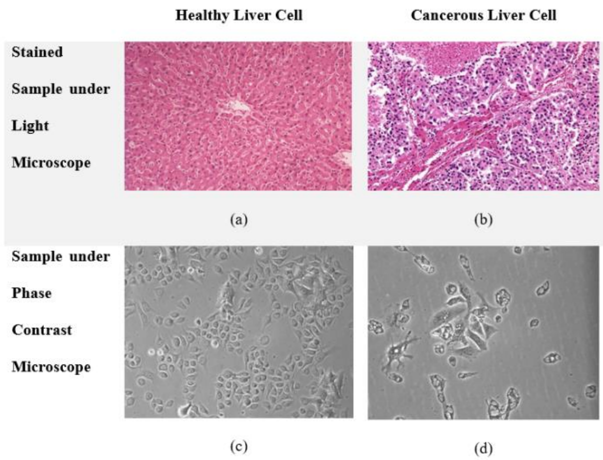

Figure 4. Cell sample images used in the educational module: a) healthy liver cell sample under the light microscope Koriem and Soliman [38], b) cancerous liver cell sample under the light microscope Davidson [39], c) healthy liver cell sample under phase contrast microscope (authors), d) cancerous liver cell sample under phase contrast microscope (authors)

Source: See caption

Participants

Anyone who met the criteria was eligible to participate in this study. The participants registered by filling in a Google Form which required the applicants to specify their personal information, educational background, and other details. According to the eligibility criteria, the participants had to be in normal mental health conditions, and they had to be able to read and understand the modules in English.

A total of 104 18-year-old science students participated in the study. While the sample was specific to pre-university science students, this demographic represents a critical transition period where abstract biological concepts such as cell morphology become increasingly complex. This makes it an ideal setting for testing AR interventions.

A non-randomized pre and post-test quasi-experimental research was conducted exclusively on Android device users. None of the students had prior exposure to cancerous liver cells images or the educational module. Ethical approval was obtained before data collection (UM.TNC2/UMREC_1113).

Experimental setup

This study involved three groups of students: group A served as the control, Group B worked with the conventional video module, and group C engaged in the AR-based module. The online learning sessions were conducted separately, following the assigned groups, with the presence of an instructor. The flow of sessions for all groups is shown in Fig. 5.

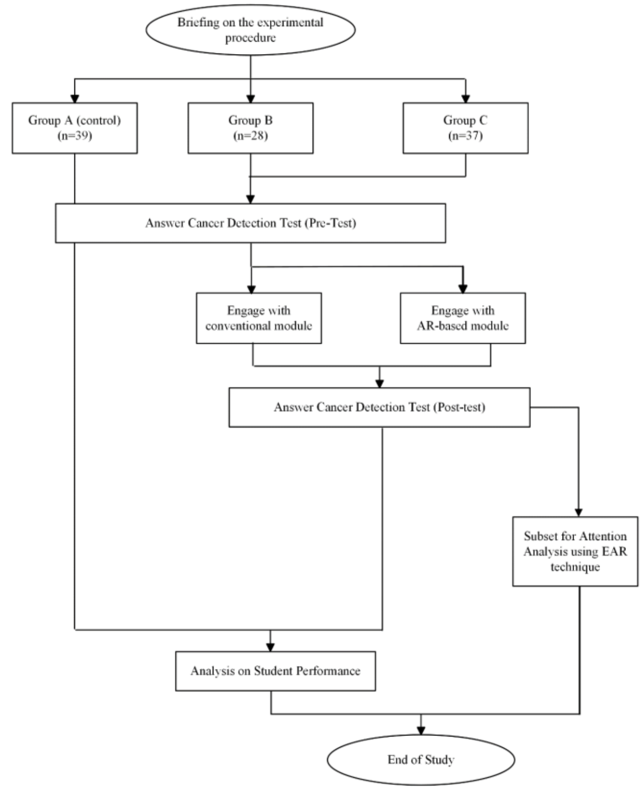

Figure 5. Experimental flow for participants in the online study session
Source: Authors

At the beginning of the session, the students in groups A, B, and C were given a pre-test in which they were required to correctly identify the images of cancerous liver cells. After the pre-test, the students in group B were instructed using the conventional module. As for group C, the students were required to download the developed AR-based mobile application provided by the instructor before engaging in the module. Both groups worked independently with their modules for ten minutes. After completing the modules, groups B and C were given the same set of test questions.

The primary assessment of cognitive performance involved the entire cohort of 104 participants to ensure generalizability across the target demographic. Meanwhile, the analysis of physiological attention utilized a nested case-study design. A subset of test participants from group C was selected for an EAR analysis based on data quality inclusion criteria. These criteria required (i) consistent lighting conditions allowing the Face Mesh algorithm to detect facial landmarks, especially in the eye area, and (ii) continuous visibility of the participant's frontal face, without any occlusion at critical times (T0 and T10).

This subset of ten participants met the recommended sample size for intensive physiological monitoring in exploratory educational technology research. It did not assume a normal distribution of EAR values, which allowed for a robust statistical analysis of attention level shifts before and after exposure.

The entire study session was recorded using the Open Broadcaster Software (OBS). From the recording, a 10 s video clip was extracted, showing the appearance of AR elements at specific points in time (T0, pre-exposure; T10, post-exposure). The lesson was divided into two periods, each lasting five minutes. During each interval, AR elements appeared four times in the mobile application. Fig. 6 depicts the timeline of AR element appearance throughout the study session.

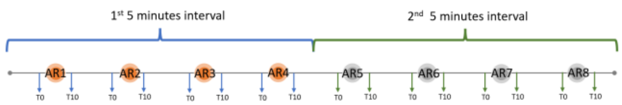

Figure 6. Timeline of AR appearance for the experimental group during the study
Source: Authors

Data analysis

In this study, data analysis was divided into two tasks: student performance analysis and attention level measurement.

Student's performance analysis

The pre- and post-test scores were analyzed based on the number of correct answers. The accuracy of the participants' answers was calculated using Eq. (1).

$$\boldsymbol{Accuracy} = \frac{\textbf{True Positive}}{\textbf{True Positive+False Negative}} \tag{1}$$

Next, we computed the mean and standard deviation of the scores for each test. To compare the pre-test scores between groups A and B and groups A and C, as well as the post-test scores between groups B and C, we performed an independent sample t-test. For groups B and C, we used a paired sample t-test to determine the statistical significance of the pre- and post-test scores. A p-value of < 0.05 was considered statistically significant.

Attention level analysis

To analyze the data for EAR calculation, the 10 s clips of each AR appearance were converted into .jpg images, with each second corresponding to a separate image. The processed images were then analyzed for landmark point detection by employing the Face Mesh algorithm, which was employed to identify specific points of interest in the image. Initially, we imported all the necessary libraries for detecting these points. After that, we executed the Face Mesh function on the imported images, which yielded a 3D mesh made up of 468 landmarks corresponding to the face present in the image. An example of such a face mesh is shown in Fig. 7.

Figure 7. A face mesh extracted from a processed image
Source: Authors

From all 468 points in the mesh, six points of interest were selected on both sides of the eye area [40], as shown in Fig. 8.

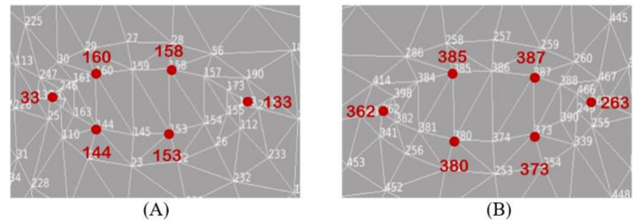

Figure 8. Points of interest for landmark detection in right eye (a) and the left eye (b)
Source: Authors

These points were used to calculate the EAR for attention analysis. The EAR formula was based on the ratio of the average vertical distance between the upper and lower eyelids (labeled in red) to the eye's horizontal distance or eye width (yellow). This is shown on Fig. 9.

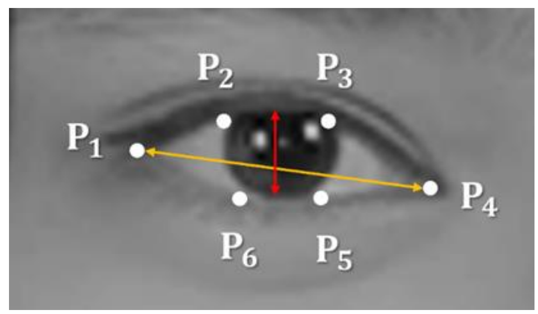

Figure 9. Points of interest in the eyes
Source: Authors

Eq. (2) provides the formula for calculating the EAR [41].

$$EAR = \frac{\| p_2 - p_6 \| + \| p_3 - p_5 \|}{2 \| p_1 - p_4 \|} \tag{2}$$

The T0 (pre-exposure) and T10 (post-exposure) data were compared using the Wilcoxon signed-rank test to maintain statistical rigor despite the smaller sample size. If the obtained p-value was lower than 0.05, the data were considered to be statistically significant [42].

Results

Demographic analysis

A total of 104 science students participated in our research. Table 1 shows the demographic information of the participants. All participants were 18 years old during this study. 65 out of 104 students were male (62.5%), which makes them the majority in comparison with the female students (n=39, 37.5%).

Table I. Demographic summary of participants

		Count (N=104)	Percentage (%)
Gender	Male	65	62,5
	Female	39	37,5

Source: Authors

Pre- and post-test performance analysis

The accuracy value was calculated using Eq. (1) for each question answered in the pre- and post-tests. The results are shown in Tables II, III, and IV for groups A (control), B, and C, respectively.

Table II. Accuracy (highlighted in yellow) of the correct answers (green) for the control groups

Group A (control) (N=34)									
Question	**Stained-cell image**				**Phase contrast image**				**Total**
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	
Yes	13	19	28	18	19	25	28	12	162
No	21	15	6	16	15	9	6	22	110
Total	34	34	34	34	34	34	34	34	272
Total correct	13	15	6	18	15	25	28	22	**142**
Total wrong	21	19	28	16	19	9	6	12	**130**
Accuracy	**0.38**	**0.44**	**0.18**	**0.53**	**0.44**	**0.74**	**0.82**	**0.65**	**0.52**

Source: Authors

Table III. Accuracy (highlighted in yellow) of the correct answers (green) for group B (conventional module)

Group B (pre-test) (N=28)									
Question	**Stained-cell image**				**Phase contrast image**				**Total**
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	
Yes	7	14	19	17	10	18	20	12	117
No	21	14	9	11	18	10	8	16	107
Total	28	28	28	28	28	28	28	28	224
Total correct	7	14	9	17	18	18	20	16	**119**
Total wrong	21	14	19	11	10	10	8	12	**105**
Accuracy	**0.25**	**0.50**	**0.32**	**0.60**	**0.64**	**0.64**	**0.71**	**0.57**	**0.53**

Group B (post-test) (N=28)									
Question	**Stained-cell image**				**Phase contrast image**				**Total**
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	
Yes	10	6	23	19	5	28	27	1	119
No	18	22	5	9	23	0	1	27	105
Total	28	28	28	28	28	28	28	28	224
Total correct	10	22	5	19	23	28	27	27	**161**
Total wrong	18	6	23	9	5	0	1	1	**63**
Accuracy	**0.36**	**0.79**	**0.18**	**0.68**	**0.82**	**1.00**	**0.96**	**0.96**	**0.72**

Source : Authors

Table IV. Accuracy (highlighted in yellow) of the correct answers (green) for group C (AR-based module)

Group C (pre-test) (N=37)									
Question	**Stained-cell image**				**Phase contrast image**				**Total**
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	
Yes	14	23	26	21	12	21	24	7	148
No	23	14	11	16	25	16	13	30	138
Total	37	37	37	37	37	37	37	37	296
Total correct	14	14	11	21	25	21	24	30	**160**
Total wrong	23	23	26	16	12	16	13	7	**136**
Accuracy	**0.38**	**0.38**	**0.30**	**0.57**	**0.68**	**0.57**	**0.65**	**0.81**	**0.54**

Group C (post-test) (N=37)									
Question	**Stained-cell image**				**Phase contrast image**				**Total**
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	
Yes	14	14	23	13	9	31	31	7	142
No	23	23	14	24	28	6	6	30	154
Total	37	37	37	37	37	37	37	37	296
Total correct	14	23	14	13	28	31	31	30	**184**
Total wrong	23	14	23	24	9	6	6	7	**112**
Accuracy	**0.38**	**0.62**	**0.38**	**0.35**	**0.76**	**0.84**	**0.84**	**0.81**	**0.62**

Source: Authors

The mean pre-test scores for groups B and C were compared against those of the control group, as shown in Table V.

Table V. Descriptive analysis of the pre-test scores for groups B and C *vs.* the control. SD = standard deviation.

	Test score	
	Mean	SD
Group A (control)	4.18	1.31
Group B (conventional)	4.25	1.62
Group C (AR)	4.32	1.31

Source: Authors

There were no significant differences between groups A (M=4.18, SD=1.31, N=34) and B (M=4.25, SD=1.62, N=28), as well as between groups A (M = 4.18, SD=1.31, N=34) and C (M=4.32, SD=1.31, N=37) in terms of pre-test scores.

Table VI shows the mean pre- and post-test scores for groups B and C. Both groups exhibited significant improvements in their mean test scores. However, there was no significant difference in the post-test scores of groups B and C. Cohen's ∂ value was calculated for the post-test scores of the two groups, indicating a preference for the conventional module over the AR alternative, with a value of 0.38.

Table VI. Mean and standard deviation of pre- and post-test results for groups B and C.

	Pre-test*		Post-test*	
	Mean	SD	Mean	SD
Group B (conventional)	4.25	1.62	5.75	1.04
Group C (AR)	4.32	1.31	5.24	1.53

* Significant changes were observed (p<0.05) in the pre-post test results for both groups

Source: Authors

Attention level analysis

The mean and standard deviation of the EAR value from the subset of group C is shown in Table VII. A total of 40 data points corresponding to T0 (pre-exposure) and T10 (post-exposure) were collected from both the left and right eyes of all ten subjects in the first half of the 5 min interval. For the second half of the interval, a total of 39 data points were collected from all ten subjects, except for one missing data point for AR6, which could not be extracted.

Table VII. Mean and standard deviation of the EAR values for ten participants in group C

	First 5 min interval (AR1-AR4)				Second five min interval (AR5-AR8)			
	Right eye*		Left eye		Right eye		Left eye	
	T0 (N=40)	T10 (N=40)	T0 (N=40)	T10 (N=40)	T0 (N=39)	T10 (N=39)	T0 (N=39)	T10 (N=39)
Mean	0.301	0.291	0.296	0.288	0.313	0.318	0.316	0.322
SD	0.081	0.082	0.073	0.077	0.082	0.079	0.083	0.074

* Significant changes were observed ($p<0.05$)

Source: Authors

All mean EAR values, either at T0 or T10, were greater than 0.25. This proves that all ten participants were paying attention and not dozing off during the engagement [31]. The results also revealed that the mean EAR value for the right eye changed significantly within the first five minutes of exposure to the AR images ($p<0.05$) and remained stable during the following five minutes.

Discussion

Cancer cell detection can be challenging for students without prior knowledge. The developed module focuses on teaching students to distinguish cancerous from healthy liver cells based on their characteristics. It emphasizes the size and shape of cells and nuclei as well as their arrangement. This module is distinct from other modules focusing on different types of cancer, *e.g.*, breast cancer [11], prostate cancer [12], and brain tumors [13].

Real cell samples were employed to expose students to the microscopic appearance of well-differentiated cancerous and healthy liver cells. Cancerous cells typically exhibit finely granular eosinophilic cytoplasm, round nuclei with dispersed chromatin, and prominent nucleoli [36]. In contrast, healthy cells have a granular cytoplasm, prominent nucleoli, and a round, centrally placed nucleus [37]. By incorporating real cell samples in the AR module, this study offers a cost-effective and accessible alternative to expensive tools like physical microscopes [43] and smart glasses [44].

The post-test results indicate that students were more successful in detecting cancerous cells using phase contrast images in comparison with their stained counterparts. This may be attributed to the use of live cell samples in phase contrast microscopy, which yields images with distinct light and dark features, highlighting differences in cell and structure as well as nucleus size [45]. Conversely, stained cell samples are often more suitable for studying metabolic processes and the effects of cell treatments [46].

This study aimed to determine whether an AR-based educational module could outperform conventional methods for cancer cell characterization, specifically in online learning. Contrary to the initial hypothesis, the results showed no significant differences between the mean performance scores of the conventional and AR groups. However, both groups exhibited significant improvement in pre- and post-test performance following their corresponding interventions.

These findings align with previous research works by Erbas and Demirer [47] and Herbert, et al. [48], which suggest that, while AR is an effective pedagogical tool, it does not always yield better results in terms of student performance than the conventional method. Likewise, Zumbach, et al. [49] found that a text-based learning group obtained higher scores than the AR counterpart in the pre- and post-tests, while the immersion level during the lesson was higher in the latter. Additionally, Lin, et al. [50] found no correlation between attention levels and student performance in AR-based studies. This indicates that the primary value of AR in pedagogy comes in the form of a 'cognitive hook' rather than entirely replacing conventional teaching methods [10].

While academic performance was comparable to the conventional method, the attention analysis conducted using the EAR revealed that AR can successfully sustain student attention, particularly during the initial five minutes of engagement. All participants maintained an EAR above the drowsiness threshold of 0.25. This finding is similar to that of a study that demonstrated the effectiveness of AR-based modules in capturing student attention within online learning environments [51].

An interesting incidental finding showed a significant change in the right eye's EAR compared to the left one. This observation may be linked to the dominance of the right eye, as it tends to be linked to the right hemisphere of the brain, which can process visual inputs more effectively than the left one [52]. Eye dominance, or ocular dominance, refers to the tendency to favor one eye over the other, especially when presented with conflicting visual information. The significant changes in the right EAR suggest that the right eye was more actively involved in processing the visual stimuli than the left one [53]. However, future studies should examine ocular dominance to confirm this correlation.

A key limitation of this study is the scope of the attention analysis. The EAR technique was applicable to the AR group, but not to the conventional group due to data collection constraints. As a result, a direct comparison between the AR and conventional modules was not possible. This study mainly validated the use of MediaPipe's Face Mesh algorithm as a non-intrusive tool for attention monitoring in AR learning within online settings, and it demonstrates the feasibility of extracting behavioral data without expensive physiological sensors. To establish the generalizability of these findings, future research should apply the EAR framework to both AR and conventional groups.

It should be noted that the online study environment could adversely affect the performance of participants who engaged with the AR-based educational module. Technical issues can arise while using the mobile application, especially if the participants are studying the module independently, without the instructor's direct supervision. While AR is known for its feasibility in independent or remote study, we cannot rule out the possibility of technical issues arising while using the AR mobile application which could hinder the learning process. The remote and independent nature of the AR-based module means that the instructor may not be aware of issues such as poor internet connectivity or low sensitivity of AR markers, leading to failures in detect the markers and properly displaying the educational material [54]. Similar issues with AR markers were identified in Weng, et al. [55], where students reported distractions during AR module engagement due to slow responsiveness. Therefore, it is essential to improve the AR markers to reduce distractions during learning sessions and ensure an uninterrupted learning experience for the students.

In a similar approach implementing AR apps in cell studies, Özeren and Top [56] found that using AR-based modules leads to increased academic achievement and motivation among students. However, the cited study employed an AR application as additional material to the regular course, unlike our module, which solely provides information through the AR tool. In another study, Omurtak and Zeybek [57] used an AR app to explain cellular structures to students with the guidance of their teachers. In this vein, the use of AR-based applications in self-paced cell study could be further explored by improving information delivery methods or providing guidance on how to use AR apps effectively.

Conclusion

In conclusion, this study confirms the effectiveness of the AR-based educational module in characterizing hepatic cancer cells within an online learning environment. The AR intervention demonstrated comparable effects on students' performance in pre- and post-tests when compared to the conventional module, validating its potential as a robust pedagogical tool for visualizing complex microscopic entities.

Crucially, the attention analysis via the EAR revealed that the AR-based module effectively captured and sustained student attention above the cognitive engagement threshold (EAR>0.25), particularly within the first five minutes. We believe that, by combining effective knowledge transfer with interactivity, this approach can provide a scalable and affordable solution for teaching complex biology topics, such as cancer cell characterization, in online education settings.

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CRediT author statement

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Conflicts of interest

The authors of this paper declare that they have no conflicts of interest.

Access to research data

The datasets generated and/or analyzed during this study are available from the authors upon reasonable request.

Statement on artificial intelligence

The authors did not use IAG. The authors take full responsibility for the contents of this publication.

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