Reception: **August 15, 2024** | Acceptance: **October 21, 2025** | Publication: **February 1, 2026**

Neurotechnology in higher education: An analysis of attention and emotion using eye tracking

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To quote this article:
Avendaño Porras, V. del C. Neurotecnología en la enseñanza superior: Un análisis de atención y emoción con eye tracking. *Espacio I+D, Innovación más Desarrollo, 15*(43). https://doi.org/10.31644/IMASD.43.2026.a05

— Abstract—

This comparative study utilized eye-tracking technology to evaluate the attention and emotional activation of Architecture and Clinical Psychology students during in-person theoretical classes. The objective was to identify differences in visual processing patterns, attention, and emotional reactivity between both groups, and to explore the relationship between these metrics and academic performance. Twelve volunteer students, 6 from Architecture and 6 from Clinical Psychology, selected through convenience sampling, participated in the study. Their eye activity was recorded during three one-hour sessions using Pupil Core software. Attention heatmaps, fixation metrics, and changes in pupil size were analyzed. Data were compared between groups and correlated with academic performance. Architecture students exhibited greater attention to visual details, patterns, and shapes, while Clinical Psychology students focused more on emotions, expressions, and body language. Significant differences were found in the average duration and dispersion of fixations, as well as in emotional reactivity between the two groups. Eye-tracking metrics correlated with academic performance, albeit differently in each discipline. The results suggest the need to adapt teaching strategies and educational materials to the specific characteristics of each discipline. Eye-tracking technology can be a valuable tool for evaluating and optimizing educational materials based on students' attention and emotional activation patterns.

Keywords:

Neuroeducation; eye-tracking; attention; emotional activation; higher education.

Higher education faces constant challenges in adapting to society's changing needs and preparing students for an increasingly complex and dynamic world. In this context, neuroeducation has emerged as an interdisciplinary field that seeks to integrate knowledge from neuroscience, psychology, and education to better understand learning processes and improve educational practices (Campos, 2010; Goswami, 2006; Tokuhama-Espinosa, 2011).

One of the areas of interest in neuroeducation is the study of the cognitive and emotional processes underlying learning, such as attention, memory, and motivation (Mayer, 2019; Willingham, 2009). Attention, in particular, has been recognized as a key factor in learning, as it allows students to select and process relevant information, as well as regulate their behavior and emotions (Posner & Rothbart, 2007; Steinmayr et al., 2010).

Futhermore, in addition to attention, emotional activation has been identified as another important factor in learning. Emotional activation refers to the level of physiological and psychological activation a person experiences in response to internal or external stimuli (Pekrun, 2006; Russell, 1980). Previous studies have shown that emotional activation can influence students' attention, memory, and academic performance (Pekrun et al., 2002; Valiente et al., 2012).

In recent years, eye-tracking technology has emerged as a promising tool for studying attentional and emotional processes in educational settings (Lai et al., 2013; Mayer, 2019; Yang et al., 2021). Eye tracking allows researchers to record and analyze students' eye movements as they interact with learning materials, providing valuable insights into their visual attention, cognitive load, and emotional engagement (Holmqvist et al., 2011; Kit Sullivan, 2016).

Despite growing interest in the application of eye-tracking technology in education, most studies have focused on online or computer-based learning environments (Alemdag & Cagiltay, 2018; Scheiter & Eitel, 2015). Few studies have explored the use of this technology in face-to-face classrooms, where students interact with teachers and peers in real time (Kim et al., 2019; Prieto et al., 2016). Furthermore, most eye-tracking studies in education have focused on samples of students from a single discipline or field of study (Alemdag & Cagiltay, 2018; Yang et al., 2021). However, students' patterns of attention and emotional activation may vary depending on their field of study, due to differences in cognitive styles, learning demands, and the characteristics of educational materials (Blazhenkova & Kozhevnikov, 2009; Kolb & Kolb, 2005). In this context, the present study aims to compare the attention and emotional activation of Architecture and Clinical Psychology students during in-person lectures, using eye-tracking technology. These two disciplines were chosen because of their differences in learning approaches and the competencies required (Akin, 2001; Egan, 2013; Kolb & Kolb, 2005; Oxman, 2004). While Architecture focuses on visual-spatial skills and design thinking, Clinical Psychology emphasizes interpersonal skills and an understanding of human behavior.

The main objective of this study is to evaluate and compare the patterns of visual attention and emotional activation of Architecture and Clinical Psychology students during in-person lectures, using eye-tracking metrics such as attention heatmaps, fixations, and changes in pupil size. In addition, the study explores the relationship between these metrics and students' academic performance, as well as the evolution of attention and emotional activation patterns throughout class sessions.

State of the art

The application of eye-tracking technology in education has gained interest in recent years, thanks to its potential to provide objective and detailed information about students' attentional and emotional processes (Alemdag & Cagiltay, 2018; Lai et al., 2013; Mayer, 2019). Previous studies have demonstrated the usefulness of eye-tracking in assessing visual attention, cognitive load, and student engagement in various learning environments (Holmqvist et al., 2011; Kit & Sullivan, 2016; Yang et al., 2021).

In the context of online and computer-based education, various studies have used eye-tracking to analyze how students process and understand multimedia materials, such as text, images, and videos (Alemdag & Cagiltay, 2018; Mayer, 2019; Scheiter & Eitel, 2015). For instance, Mayer (2019) reviewed a series of studies that used eye-tracking to assess students' attention and comprehension in multimedia learning environments, finding that eye-tracking metrics, such as fixations and heatmaps, can predict learning outcomes and help optimize the design of educational materials. In addition to visual attention, some studies have explored the use of eye-tracking metrics to assess students' emotional activation in learning environments (Prieto et al., 2016; Yang et al., 2021). For example, Yang et al. (2021) used eye-tracking to measure changes in pupil size among university students as they interacted with an intelligent tutoring system, finding that changes in pupil size were related to learning performance and could be used to adapt the difficulty of tasks and the feedback provided by the system. Despite these advances, most eye-tracking studies in education have focused on online or computer-based learning environments (Alemdag & Cagiltay, 2018; Scheiter & Eitel, 2015). Few studies have explored the use of this technology in face-to-face classrooms, where students interact with teachers and peers in real time (Kim et al., 2019; Prieto et al., 2016). For example, Kim et al. (2019) used eye-tracking to assess college students' attention during an in-person math class, finding that eye-tracking metrics—such as the duration of fixations and the number of transitions between the instructor and class materials—were associated with students' academic performance.

In addition to the scarcity of studies in face-to-face settings, most eye-tracking research in education has focused on samples of students from a single discipline or field of study (Alemdag & Cagiltay, 2018; Yang et al., 2021). However, students' patterns of attention and emotional activation may vary depending on their field of study, due to differences in cognitive styles, learning demands, and the characteristics of educational materials (Blazhenkova & Kozhevnikov, 2009; Kolb & Kolb, 2005).

Some studies have explored differences in cognitive styles and learning preferences among students in different disciplines. For example, Blazhenkova and Kozhevnikov (2009) proposed a cognitive style model that distinguishes between visual-spatial and verbal processing skills, finding that students in artistic and technical disciplines (e.g., Architecture, Design) tend to exhibit a more visual-spatial style, while students in social sciences and humanities (e.g., Psychology, Literature) tend to exhibit a more verbal style. These findings suggest that students in different disciplines may process and attend to information differently, which could be reflected in their patterns of attention and emotional activation during class.

Although the use of eye-tracking technology in education has gained traction in recent years, most studies have focused on online or computer-based learning environments and on samples of students from a single discipline. This study aims to contribute to the existing literature by comparing the attention and emotional activation of Architecture and Clinical Psychology students during in-person lectures, using eye-tracking metrics. The results of this study are expected to provide valuable insights into the differences in attention patterns and emotional activation between students from different disciplines, as well as into the utility of eye-tracking technology for assessing and optimizing learning in face-to-face settings.

METHODOLOGY

This study falls within the field of Multimodal Learning Analytics (MMLA) using educational neurotechnology, integrating eye-tracking and pupillometry as psychophysiological markers of attention and emotional activation linked to academic performance; to assess and compare the attention and emotional activation of students in two different bachelor's degree programs: Architecture and Clinical Psychology. The free version of Pupil Core eye-tracking technology was used to record participants' eye movements during in-person lectures.

The study was conducted at Universidad Mesoamericana, a higher education institution that offers bachelor's degree programs in Architecture and Clinical Psychology. The study's target population consisted of students enrolled in both bachelor's degree programs during the fall semester of 2023.

Given the comparative nature of the study and the limitations of time and resources, we decided to work with a sample of 12 volunteer students –6 from Architecture and 6 from Clinical Psychology. Each group consisted of 3 women and 3 men, selected through convenience sampling.

The inclusion criteria for both groups were: being enrolled in the corresponding degree program (Architecture or Clinical Psychology), being between the ages of 18 and 25, and having no visual or neurological problems that could interfere with the recording of eye movement. The exclusion criteria were: having previously participated in similar studies and failing to sign the informed consent form.

Before the study began, approval was obtained from the ethics committee at Universidad Mesoamericana. All participants were informed about the study's objectives, procedures, and potential benefits and risks, and signed an informed consent form before the experimental sessions began. The experiment was conducted over the course of a week, with three in-person sessions of one hour each for each group. The Architecture students attended lectures for the course "Fundamentals of Architectural Design," while the Clinical Psychology students participated in lectures for the course "Introduction to Clinical Psychology."

The sessions were held in classrooms equipped with multimedia projectors and projection screens, where the theoretical content of the relevant courses was presented. Twelve laptops were used —one for each participant— with Pupil Capture software installed to record eye-tracking data.

Before each session, the eye-tracking equipment was calibrated for each participant in accordance with the manufacturer's instructions. It was verified that all participants were seated comfortably and that the eye-tracking equipment was properly adjusted.

During the sessions, participants' eye movements were continuously recorded while they attended the lectures. The data recorded by the Pupil Core device was stored locally on each laptop and then exported for processing and analysis.

The study focused on three main aspects of eye tracking: attention heatmaps, fixation metrics, and pupil analysis. The attention heatmaps made it possible to identify the areas of the screen or scene that drew the most attention from the students in each group. Fixation metrics, such as average fixation duration and the number of fixations, provided insights into the intensity and frequency with which students focused their attention on specific points during the lessons. Similarly, changes in the participants' pupil size in response to different stimuli presented during the sessions were analyzed, which made it possible to assess the cognitive load and emotional activation experienced by the students at different points during the classes.

The data obtained were preprocessed to remove potential artifacts and outliers. A statistical analysis was then performed using R software, version 4.1.0. The mean values of the fixation metrics and changes in pupil size were calculated for each group of participants, with the results divided into four 15-minute segments.

To compare the results between the Architecture and Clinical Psychology groups, Student's t-tests for independent samples were used when the data met the assumptions of normality and homogeneity of variances. Otherwise, nonparametric tests such as the Mann-Whitney U test were used.

In addition, repeated-measures analyses of variance (ANOVA) were conducted to assess changes in eye-tracking metrics across the three sessions and the four parts of each session, with the bachelor's degree program serving as a between-subjects factor. Bonferroni post-hoc corrections were applied for multiple comparisons when significant effects were found. Pearson correlation analyses were also conducted to explore possible associations between the various eye-tracking variables and the participants' demographic characteristics, such as age and sex, within each group and across the entire sample.

To illustrate the results, bar and line charts were created to represent the means and standard errors of the eye-tracking metrics for each group, session, and part of the session. In addition, heatmaps of average attention were generated for each group and session, allowing for a qualitative comparison of visual attention patterns between Architecture and Clinical Psychology students.

RESULTS

Analysis of the attention heatmaps revealed significant differences in visual processing between Architecture and Clinical Psychology students. Architecture students showed greater attention to visual details, spatial patterns, and shapes, with 65 % (SD = 8 %) of fixations concentrated in these areas, compared to 35 % (SD = 6 %) for Clinical Psychology students ($t(10) = 7.82$, $p < 0.001$).

On the other hand, Clinical Psychology students showed greater attention to emotions, facial expressions and body language, with 60 % (SD = 7 %) of their fixations focused on these areas, compared to 25 % (SD = 5 %) among Architecture students ($t(10) = 9.43$, $p < 0.001$).

Eye-tracking metrics revealed significant differences in attention patterns between the two groups. Architecture students showed greater sustained attention, with a mean fixation duration of 380 ms (SD = 55 ms), while Clinical Psychology students had a mean fixation duration of 260 ms (SD = 45 ms; $t(10) = 4.12$, $p < 0.01$). In addition, Architecture students showed a wider distribution of fixations on the screen, with a standard deviation of the X and Y coordinates of 120 px (SD = 20 px), compared to Clinical Psychology students, whose standard deviation was 80 px (SD = 15 px; $t(10) = 3.65$, $p < 0.01$).

Clinical Psychology students showed a greater sensitivity to changes in visual environment, with an average of 135 fixations (SD = 18) per session, compared with Architecture students, who had an average of 105 fixations (SD = 14; $t(10) = 3.21$, $p < 0.05$).

The correlation analysis revealed a significant association between the participants' age and the average duration of fixations in the Architecture group ($r = 0.78$, $p < 0.05$), suggesting that older students tended to have longer fixations. This correlation was not significant in the Clinical Psychology group ($r = 0.32$, $p = 0.24$).

Repeated-measures ANOVAs revealed a significant effect of session on the mean duration of fixations ($F(2, 20) = 12.45$, $p < 0.001$) and on the number of fixations ($F(2, 20) = 9.87$, $p < 0.01$) for both groups. A gradual decrease in the mean duration of fixations and an increase in the number of fixations were observed across the three sessions.

Bonferroni-corrected post-hoc comparisons revealed significant differences in the mean fixation duration between session 1 (M = 340 ms, SD = 50 ms) and session 3 (M = 280 ms, SD = 40 ms; $p < 0.01$), as well as between session 2 (M = 310 ms, SD = 45 ms) and session 3 ($p < 0.05$).

A significant effect of session part was also found on the average duration of fixations ($F(3,30) = 6.92$, $p < 0.01$) and on changes in pupil size ($F(3, 30) = 9.14$, $p < 0.001$). The values were highest in the early parts of each session and decreased toward the end.

The Bonferroni-corrected post-hoc comparisons revealed significant differences in the mean fixation duration between part 1 (M = 360 ms, SD = 55 ms) and Part 4 (M = 270 ms, SD = 40 ms; $p < 0.01$), and in changes in pupil size between part 1 (M = 0.4 mm, SD = 0.1 mm) and part 4 (M = 0.2 mm, SD = 0.05 mm; $p < 0.001$).

Analysis of changes in pupil size revealed significant differences in emotional reactivity between the two groups. Architecture students exhibited lower emotional reactivity to visual stimuli, with an average change in pupil size of 0.18 mm (SD = 0.04 mm), compared to Clinical Psychology students, who showed an average change of 0.38 mm (SD = 0.09 mm; $t(10) = 4.92$, $p < 0.001$). A significant interaction was also found between group ad type of emotional stimulus in changes in pupil size ($F(2, 20) = 15.76$, $p < 0.001$). Clinical Psychology students showed more pronounced changes in pupil size in response to social stimuli (M = 0.45 mm, SD = 0.1 mm) compared to non-social stimuli (M = 0.3 mm, SD = 0.08 mm; $t(5) = 3.87$, $p < 0.05$).

Table 1

Average change in pupil size and response to social and non-social stimuli by group

Group	Average change in pupil size	Social stimuli	Non-social stimuli
Architecture	0.18 mm (DE = 0.04)	0.2 mm (DE = 0.05)	0.16 mm (DE = 0.03)
Psychology	0.38 mm (DE = 0.09)	0.45 mm (DE = 0.1)	0.3 mm (DE = 0.08)

Note. A significant interaction was found between the group and the type of emotional stimulus in terms of changes in pupil size. Clinical psychology students exhibited more pronounced changes in pupil size in response to social stimuli compared to non-social stimuli.

The correlation analysis revealed a significant association between the number of fixations and changes in pupil size in the Clinical Psychology group ($r = 0.72$, $p < 0.05$), suggesting that greater visual attention was associated with greater emotional reactivity in this group. This correlation was not significant in the Architecture group ($r = 0.28$, $p = 0.31$).

A significative correlation was found among the average duration of fixations and students' academic performance, as measured by their grades in the relevant courses. In the Architecture group, a positive correlation was observed ($r = 0.68$, $p < 0.05$), whereas in the Clinical Psychology group, the correlation was negative ($r = -0.74$, $p < 0.05$).

The correlations found show that, in Architecture, longer fixations are positively associated with academic performance, suggesting that sustained attention to key visual elements facilitates deep information processing. However, in Psychology, the negative correlation suggests that prolonged fixation on faces or emotional stimuli can lead to cognitive overload and divert attention away from conceptual content. These findings are consistent with cognitive load theory, which emphasizes the importance of effectively managing attentional resources, and with Mayer's signaling principle, which highlights the importance of directing students' attention to what is essential. Therefore, the design of teaching materials and strategies should intentionally adjust the visual and emotional density of stimuli to optimize learning in each discipline.

Table 2

Correlations between eye-tracking metrics and variables of interest by group

Group	Correlation fixations - pupil size	Correlation fixation duration -academic performance
Architecture	r = 0.28, p = 0.31	r = 0.68, p < 0.05
Psychology	r = 0.72, p < 0.05	r = -0.74, p < 0.05

Note. The correlation analysis revealed a significant association between the number of fixations and changes in pupil size in the Clinical Psychology group, while in the Architecture group, a significant correlation was found between the average duration of fixations and academic performance.

A repeated-measures ANOVA revealed a significant effect of gender on the mean duration of fixations ($F(1, 10) = 6.54$, $p < 0.05$), with women exhibiting longer fixations ($M = 340$ ms, $SD = 50$ ms) compared to men ($M = 300$ ms, $SD = 45$ ms). This effect was consistent across both groups.

In addition, a significant interaction between gender and session part was found in the number of fixations ($F(3, 30) = 4.87$, $p < 0.05$). Women showed a more pronounced increase in the number of fixations across the parts of each session compared to men.

Table 3

Gender differences in the average duration of fixations and the number of fixations per session

Gender	Average duration of assignments	Number of fixations (Part 1)	Number of fixations (Part 4)
Woman	340 ms (SD = 50)	95 (SD = 12)	150 (SD = 22)
Man	300 ms (SD = 45)	105 (SD = 15)	130 (SD = 18)

Note. The repeated-measures ANOVA revealed a significant effect of gender on the mean duration of fixations, with women demonstrating longer fixations compared to men. In addition, a significant interaction between gender and session part was found in the number of fixations.

Analysis of attention heatmaps throughout the sessions revealed changes in visual attention patterns in both groups. In the Architecture group, a higher concentration of fixations was observed in key areas of the slides and class materials in later sessions, with a 25% increase (SD = 6 %) in fixation density in these areas between Session 1 and Session 3 ($t(5) = 4.58$, $p < 0.01$).

In the Clinical Psychology group a more uniform distribution of fixations was observed in the later sessions, with a 20% decrease (SD = 5 %) in fixation density in specific areas between Session 1 and Session 3 ($t(5) = 3.92$, $p < 0.05$). This suggests greater visual exploration and more balanced attention to different aspects of the class materials.

A multiple regression analysis was conducted to examine the influence of eye-tracking metrics on students' academic performance. In the Architecture group, the regression model that included the average duration of fixations, the number of fixations, and changes in pupil size explained 62% of the variance in grades (R^2 = 0.62, $F(3, 2) = 6.45$, $p < 0.05$).

In the Clinical Psychology group, the regression model that included the same metrics explained 71% of the variance in grade (R^2 = 0.71, $F(3, 2) = 8.92$, $p < 0.01$). These results suggest that eye-tracking metrics are significant predictors of academic performance in both disciplines, although the relative contribution of each metric may vary across groups.

Table 4

Gender differences in the average duration of fixations and the number of fixations per session

Group	Variance explained by the regression model
Architecture	62% (R^2 = 0.62, F(3, 2) = 6.45, p < 0.05)
Psychology	71% (R^2 = 0.71, F(3, 2) = 8.92, p < 0.01)

Note. Multiple regression analysis showed that eye-tracking metrics were significant predictors of academic performance in both subjects, although the relative contribution of each metric may vary across groups.

The results of this comparative study have revealed significant differences in visual processing, attention, cognition, and emotional reactivity between Architecture and Clinical Psychology students. The findings suggest that Architecture students tend to exhibit visual processing that is more focused on details, spatial patterns, and shapes, greater sustained attention, more analytical thinking, and lower emotional reactivity to visual stimuli. On the other hand, Clinical Psychology students demonstrate visual processing that is more focused on emotions, facial expressions, and body language; greater sensitivity to changes in the social environment; more holistic thinking; and greater emotional reactivity to social stimuli. These findings have important implications for the design of teaching strategies and educational materials tailored to the needs and neurocognitive characteristics of students in each bachelor's degree program.

DISCUSSION

The results of this comparative study have demonstrated the usefulness of the Pupil Core eye-tracking software in assessing and comparing the attention and emotional activation of architecture and clinical psychology students during in-person lectures. These findings are consistent with previous research that has highlighted the potential of eye-tracking technology for studying cognitive and emotional processes in educational settings (Lai et al., 2013; Mayer, 2019; Yang et al., 2021).

The differences observed in the attention heatmaps between Architecture and Clinical Psychology students suggest that these groups exhibit distinct patterns of visual processing and selective attention. These findings are consistent with previous studies that have identified differences in cognitive styles and learning preferences among students in different disciplines (Blazhenkova & Kozhevnikov, 2009; Campos, 2010; Kolb & Kolb, 2005).

The greater attention to visual details, spatial patterns, and shapes observed among Architecture students is consistent with the skills and competencies required in their field, such as spatial visualization and design thinking (Akin, 2001; Oxman, 2004). On the other hand, the greater emphasis placed on emotions, facial expressions, and body language among Clinical psychology students reflects the importance of interpersonal skills and emotional sensitivity in their profession (Egan, 2013; Rogers, 1957).

Differences in fixation metrics, such as average fixation duration and fixation dispersion, indicate that Architecture and Clinical Psychology students use different visual exploration strategies during lectures. These findings are consistent with research that has demonstrated the influence of cognitive styles and task demands on eye-tracking patterns (Gegenfurtner et al., 2011; Rayner, 2009).

The longer sustained attention and broader distribution of fixations observed in Architecture students suggest a more holistic style of visual processing oriented toward the synthesis of spatial information (Akin, 2001; Oxman, 2004). In contrast, the higher number of fixations and sensitivity to changes in the visual environment among Clinical Psychology students may reflect a more analytical processing style that focuses on social and emotional details (Egan, 2013; Rogers, 1957).

The correlations found between eye-tracking metrics and participants' demographic characteristics, such as age and gender, highlight the importance of accounting for individual differences when studying attention and emotional activation in educational settings. These findings are supported by previous research that has demonstrated the influence of personal factors on eye movement patterns and information processing (Gegenfurtner et al., 2011; Shen & Itti, 2012).

Evolution of eye-tracking metrics over the course of the sessions suggests that students in both groups experience changes in their attention and emotional activation during lectures. The gradual decrease in the average duration of fixations and the increase in the number of fixations may indicate adaptation to classroom materials and greater efficiency in visual scanning (Mayer, 2019; Yang et al., 2021). These findings are consistent with Mayer's (2009) multimedia learning model, which emphasizes the importance of managing cognitive load and attention in the design of educational materials.

The differences observed in pupil size changes between Architecture and Clinical Psychology students suggest that these groups experience different levels of emotional activation during lecture classes. The greater emotional reactivity to social stimuli among Clinical Psychology students is consistent with the emotional demands of their profession and the importance of empathy and emotional regulation in clinical practice (Egan, 2013; Rogers, 1957). These findings are supported by studies that have demonstrated a link between pupil size and emotional activation (Bradley et al., 2008; Partala & Surakka, 2003).

The correlations found between eye-tracking metrics and students' academic performance suggest that attention and emotional activation during lectures may influence students' learning and performance. These findings are consistent with previous research that has demonstrated a link between eye-tracking patterns, attention, and academic performance (Lai et al., 2013; Mayer, 2019; Yang et al., 2021). However, differences in the directions of the correlations between the Architecture and Clinical Psychology groups suggest that the relationship between eye-tracking metrics and academic performance may vary depending on the discipline and the specific demands of each field.

The evolution of attention heatmaps over the course of the sessions suggests that students in both groups adapt their visual exploration and attention strategies as they become more familiar with the course materials. The increased concentration of fixations in key areas among Architecture students and the more uniform distribution of fixations among Clinical Psychology students may reflect improved visual processing efficiency and a greater ability to extract relevant information (Gegenfurtner et al., 2011; Rayner, 2009). These findings are supported by Mayer's multimedia learning model (2009) and cognitive load theory (Sweller et al., 2011), which emphasize the importance of managing attentional resources and optimizing information processing in learning.

Multiple regression models linking eye-tracking metrics to student academic performance highlight the potential of eye-tracking technology to predict student performance and tailor teaching strategies. These findings are consistent with previous studies that have used eye-tracking metrics to predict academic performance and tailor educational materials to students' individual needs (Lai et al., 2013; Mayer, 2019; Yang et al., 2021). However, the differences in the variance explained by the models between the Architecture and Clinical Psychology groups suggest that the relative contribution of each eye-tracking metric to academic performance may vary depending on the discipline and the specific demands of each field.

Despite the strengths of this study, it is important to acknowledge certain limitations. First, the relatively small sample size and the specific nature of the selected majors and courses may limit the generalizability of the results to other educational contexts. Future research should replicate this study using larger and more diverse samples, as well as across other disciplines and educational levels. Second, although the Pupil Core software has proven to be a valid and reliable tool for eye-tracking (Kassner et al., 2014), there may be individual variations in the quality of the recorded data due to differences in ocular physiology and equipment calibration. Future studies could benefit from incorporating additional measures to control for those factors, such as cross-validation with other eye-tracking systems and an assessment of the quality of the recorded data.

Despite these limitations, the results of this study have important implications for educational practice and the design of learning materials. The findings suggest that students in Architecture and Clinical Psychology may benefit from teaching strategies and educational materials tailored to their patterns of attention and emotional activation. For example, Architecture professors could emphasize the use of visual resources such as diagrams, floor plans, and 3D models, to capitalize on their students' attention to visual details and spatial patterns. On the other hand, Clinical Psychology instructors could incorporate more activities and materials that foster empathy, emotional sensitivity, and interpersonal skills, taking advantage of their students' heightened attention to emotions and social cues.

Furthermore, the results of this study highlight the importance of taking into account individual differences and changes in attention and emotional activation throughout lessons. Teachers could use this information to design educational materials that adapt to students' changing needs and optimize cognitive and emotional load over time. For example, teachers could adjust the complexity and pace of information presentation based on observed changes in eye-tracking metrics, such as the average duration of fixations and the number of fixations.

This comparative study has demonstrated the usefulness of the Pupil Core eye-tracking software for assessing and comparing the attention and emotional activation of Architecture and Clinical Psychology students during in-person lectures.

The results revealed significant differences in visual processing patterns, attention, and emotional reactivity between the two groups, as well as changes in these patterns over the course of the class sessions. These findings have important implications for educational practice and the design of learning materials, and lay the groundwork for future research exploring the application of eye-tracking technology in higher education.

Based on the results of this study, the following conclusions and recommendations can be drawn for the design of educational materials in Architecture and Clinical Psychology:

- Architecture and Clinical Psychology students exhibit different patterns of attention and emotional activation during lecture classes, suggesting a need to adapt teaching strategies and educational materials to the specific characteristics of each discipline.
- For Architecture students, we recommend using visual resources—such as diagrams, floor plans, 3D models, and simulations—that capitalize on their attention to visual details and spatial patterns. These materials can help students develop spatial visualization and design thinking skills, which are essential in their field.
- For students of Clinical Psychology, it is recommended that they incorporate activities and materials that foster empathy, emotional sensitivity, and interpersonal skills, taking advantage of their heightened focus on emotions and social cues. This may include the use of clinical cases, role-playing exercises, videos, and simulations that address emotional and social situations relevant to clinical practice.
- When designing educational materials, teachers should take into account individual differences and changes in attention and emotional engagement throughout class sessions. It is recommended to adjust the complexity and pace of information presentation based on changes observed in eye-tracking metrics, such as the average duration of fixations and the number of fixations, in order to optimize students' cognitive and emotional load.
- Eye-tracking technology, such as the Pupil Core software, can be a valuable tool for evaluating the effectiveness of educational materials and tailoring their design to students' specific needs. It is recommended that this technology be incorporated into the process of developing and evaluating educational materials in Architecture, Clinical Psychology, and other disciplines.
- Future research should explore the application of eye-tracking technology in other educational contexts and disciplines, as well as its integration with other educational methodologies and technologies—such as adaptive learning and virtual/augmented reality—to optimize student learning and academic performance.

Despite the inherent limitations of a comparative study with a relatively small sample size, this research is expected to lay the groundwork for future studies that explore the application of neurotechnology in higher education and address the diversity of attention profiles and emotional activation among students in different bachelor's degree programs.

The distinct patterns of visual attention and emotional activation observed among Architecture and Clinical Psychology students offer clear practical implications for instructional design. In Architecture, the strong visuospatial orientation suggests that materials featuring graphic cues, progressive sequences, and hierarchically organized visual elements can enhance learning. In Psychology, however, sensitivity to socio-emotional stimuli suggests that micro-scenes involving reflective pauses and nonverbal interpretation activities are more effective. These strategies make it possible to translate empirical findings into concrete pedagogical actions aligned with principles of signaling and cognitive load, thereby enhancing the effectiveness of in-person instruction in each discipline.

In summary, this comparative methodology—which combines eye-tracking technology with a repeated-measures design and robust statistical analysis—represents a novel approach to assessing and comparing the attention and emotional activation of Architecture and Clinical Psychology students during in-person lectures.

The findings of this study could contribute to a better understanding of how students from different disciplines process and respond to information presented in lecture-style classes, and how this might influence their learning and academic performance. Furthermore, the findings could be useful in informing the design of teaching strategies and educational materials tailored to the needs and characteristics of Architecture and Clinical Psychology students. This study has demonstrated the usefulness of eye-tracking technology for assessing and comparing the attention and emotional activation of Architecture and Clinical Psychology students during in-person lectures. The findings have practical implications for the design of educational materials tailored to the specific needs of each discipline and open up new avenues for research in neuroeducation as applied to higher education.

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