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Eye-tracking insights into cognitive strategies, learning styles, and academic outcomes of Turkish medicine students

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Abstract

Background Individual differences in learning preferences and cognitive strategies play a crucial role in shaping academic outcomes, emphasizing the need to customize educational approaches to meet diverse learner needs. This study explores the relationship between gaze behavior, learning style and academic performance in 20 sophomore Turkish medical students.

Methods Eye-tracking metrics, gaze duration, fixation count, fixation duration, and saccadic movements, were recorded using Tobii Pro Glasses 2 eye tracker during Trail Making, Visual Sustained Attention and the Stroop Tests and associated with the Felder-Soloman learning style and academic performance.

Results Eye-tracking data revealed consistent patterns across tasks, with fixation percentages averaging 94% and saccadic movements accounting for 6%, suggesting uniform attention allocation. Pupil diameter variation did not significantly differ between tasks, implying similar cognitive demands across all tasks. Most of the participants demonstrated moderate-to-strong visual learning preferences, particularly females. Significant gender differences were observed in learning preferences and academic performance, with higher Grade Point Averages among female participants with stronger visual learning preferences.

Conclusions The study underscores gender-based differences in learning preferences and the alignment of these preferences with academic performance. The findings suggest the importance of tailoring educational strategies to support diverse learning needs, with a particular emphasis on visually engaging materials.

Keywords Preference, Learning style, Cognitive processing speed, Pupil diameter, Cognitive load, Visual-verbal learner, Cumulative GPA

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Background

Individual differences in learning preferences and cognitive strategies significantly impact academic performance, highlighting the need for tailored educational approaches to accommodate diverse learner needs. The information processing model offers a valuable framework for understanding how individuals perceive, process, and internalize information. In educational settings, this model helps explain the relationship between cognitive behaviors—such as gaze behavior, attention, and cognitive load—and academic outcomes [1–4].

Cognitive Load Theory (CLT), proposed by Sweller [5], suggests that learning is most effective when cognitive load is optimized, with cognitive load referring to the mental effort needed to process information [5]. CLT emphasizes that different learning styles, such as visual or verbal, can influence cognitive load. Visual learners may benefit from visual materials that reduce extraneous cognitive load, while verbal learners may perform better with text-based or auditory content. The Cognitive Theory of Multimedia Learning (CTML), developed by Mayer [6, 7], extends CLT by highlighting the benefits of combining verbal and visual information in multimedia environments [6–9]. CTML asserts that dual-channel processing, where both visual and verbal channels are engaged, can improve learning outcomes if cognitive load is managed properly. This theory suggests that visual learners may perform better with multimedia materials that integrate visual and verbal content, while verbal learners may benefit more from text paired with narration. These principles can provide valuable insights into how learning styles and cognitive load interact during multimedia learning tasks.

Eye-tracking technology offers a powerful tool for exploring these cognitive processes in real-time. Metrics such as gaze duration, fixation count, fixation duration, and saccadic movements can provide detailed insights into how learners allocate their attention, how cognitive load fluctuates during task performance, and how these factors relate to academic achievement [10–13]. Studies have shown that gaze behavior is linked to cognitive load and attention, with increased fixation duration and pupil dilation often indicating higher cognitive load. Rayner et al. [14] found that low-frequency words had longer fixations than high-frequency words, even when word length was controlled [14]. Ashby et al. [15] demonstrated a correlation between eye movement measurements and reading ability, revealing that ineffective phonemic processing is linked to slower reading speeds [15]. Bayrak Karslı et al. (2020) examined how different test-taking procedures influenced reading proficiency and eye-tracking metrics, concluding that reading the question stem first did not improve achievement or dwell time [16]. The Felder-Soloman Index of Learning Styles (ILS) [17] classifies learners based on their preferences for processing information—visual, verbal, sequential, and global, which influences how cognitive resources are allocated during learning tasks [18–23]. Academic performance, typically measured by cumulative Grade Point Average (GPA), reflects how effectively these cognitive resources are utilized in learning and problem-solving contexts [15, 16]. In this context, eye-tracking data can serve as a bridge between learning styles and cognitive load theory, offering a unique lens through which to examine how students interact with learning materials and how this interaction impacts academic performance. This study explores the relationship between eye-tracking metrics, learning styles (measured by the Felder-Soloman Index), and academic performance (measured by cumulative GPA) in Turkish medical students. It aims to address key questions regarding how learning style preferences influence cognitive load and attention allocation during various cognitive tasks. By linking eye-tracking metrics with learning theories and academic performance, this study seeks to advance our understanding of how cognitive processes, such as attention and cognitive load, are influenced by individual learning preferences and how these processes affect academic outcomes. The study hypothesizes that students with strong visual learning preferences will exhibit longer fixation durations and more frequent saccadic movements compared to those with verbal or moderate preferences. Additionally, it is expected that visual learners will have higher GPAs than verbal learners, particularly among female students. Furthermore, the study hypothesizes that the cognitive demands of different tasks will not significantly alter the relationship between learning style and cognitive task performance. Visual learners are expected to show consistent eye-tracking metrics (e.g., fixation percentage) across various tasks, indicating stable cognitive processing strategies.

By integrating eye-tracking metrics with learning styles and academic performance, this study seeks to address a gap in literature where these factors are typically examined separately. This approach will uncover how cognitive processing behaviors relate to academic success and may inform the development of adaptive learning environments that cater to individual learning preferences. The findings could ultimately contribute to creating more effective, personalized educational strategies that align with the diverse cognitive and learning styles of students.

Methods

Participants

Twenty undergraduate students (mean age 24), gender: 9 Female, 11 male) participated in this study. All participants were enrolled in senior class of Faculty of Medicine at Acibadem Mehmet Ali Aydinlar University. Inclusion criteria required participants to have normal or corrected-to-normal vision and to provide informed consent prior to participation. Determination of the sample size was done with G-Power (GPower—Universität Düsseldorf) version 3.2.1. The study sample size satisfied a 95% confidence interval with two tail t-test with α err prob: 0.05, power (1-β err prob): 0.95, and effect size $|\rho|$: 0.65. Ethics committee approval was obtained.

Experimental design and procedure

Upon arrival, participants were informed about the study procedure and provided written consent. Each participant completed the Felder-Soloman Learning Style Index (ILS) to assess his/her learning preferences across four dimensions. Each dimension was scored based on a set of self-reported responses. The validated and the complete translation of the ILS into Turkish, which is called the "Turkish Index of Learning Styles" [24], was used to make the survey appropriate for Turkish participants. The English language version of the ILS can be found in the supplementary file. The ILS consists of 44 forced-choice questions, with participants choosing between two statements that align with one of the learning style categories. Participants' visual-verbal dimensions were assessed and interpreted based on their level of preference: balanced, moderate and strong. Balanced preference (Score: -3 to + 3) implied no strong inclination toward either pole of the dimension. Moderate preference (Score: ± 5 to ± 7) implied a noticeable preference for one pole, which may influence the learning style. Strong preference (Score: ± 9 to ± 11) implied a dominant preference, which dictated the learning style.

Academic performance was assessed using participants' cumulative Grade Point Average (GPA), which was obtained from institutional records. GPA scores (on a 4.0 scale) were used as a continuous variable to assess the overall academic achievement of the participants.

Eye movement data were recorded using Tobii Pro Glasses 2. This device offers a high sampling rate of 100 Hz, which allows for precise measurement of gaze metrics, including fixation duration, saccadic movements, and gaze path. The eye tracker was calibrated for each participant using a standard 5-point calibration procedure, ensuring high accuracy of gaze data. Calibration was repeated if the calibration error exceeded 1 degree of visual angle. To minimize any potential artifacts, participants were seated approximately 65 cm from the screen in a well-lit room. The Tobii Pro Lab software was used to process and analyze the raw data, which included the following key metrics: gaze duration, fixation count, fixation duration, and saccadic movements. Each task was displayed for 60 s, with 10 s breaks between tasks to reduce fatigue. The order of tasks was counterbalanced to mitigate any potential order effects. To ensure the validity of the eye-tracking data, a comprehensive validation procedure was applied. Calibration was repeated if any significant deviation from the target fixation points was observed. This approach has been validated in previous research where eye-tracking metrics correlated well with cognitive performance and learning outcomes [14, 15]. Fixation duration, saccadic movements, gaze paths, pupil diameter parameters were collected real-time.

Visual stimuli

Four tasks were designed to assess the gaze responses of the participants. These included two trail making tests (TMT-A and TMT-B), one visual sustained attention test (VSAT) and one Stroop test (Fig. 1). The TMT-A task assesses sequencing ability and cognitive flexibility. It requires participants to engage their working memory to maintain and process the sequence of numbers while visually tracking the connections. Eye-tracking metrics, such as fixation duration and saccadic movements, can reveal the level of attention and cognitive effort required to maintain the sequence. This task imposes moderate cognitive load due to the need for sustained attention and coordination. In contrast, the TMT-B task adds complexity by requiring participants to alternate between numbers and letters. This task measures cognitive flexibility and executive control, demanding greater attentional control and working memory as individuals switch between two categories. In the VSAT task, participants must detect a specific target stimulus (ladybugs) within a field of irrelevant stimuli (coffee beans). This task primarily measures sustained attention and visual processing, with cognitive load influenced by the need to maintain focus over time and filter out distractions. Eye-tracking metrics like fixation count and duration are expected to increase as participants concentrate, and saccadic movements may indicate rapid shifts in attention while scanning for the target. Finally, the Stroop test assesses executive control and inhibitory control. Participants are asked to name the color of ink in which a color word is printed, requiring them to suppress the automatic tendency to read the word and instead focus on the ink color. The cognitive load here is high, as the task engages attentional control and mental flexibility. Eye-tracking metrics, such as fixation duration and saccadic movement frequency, can reveal the effort needed to manage conflicting information and suppress automatic responses.

These tasks differ in the cognitive load they impose. Tasks that require switching between information sets, like TMT-B, or those involving inhibitory control, like the Stroop test, demand higher cognitive resources. Tasks such as TMT and Stroop also engage working memory, requiring participants to store and process sequences or conflicting information. Conversely, the VSAT primarily measures sustained attention, while TMT focuses on flexible attention.

Each task targets different aspects of cognition, and eye-tracking metrics will reflect how cognitive resources are allocated across them. Variations in attention allocation (e.g., fixation duration), visual processing (e.g., saccadic movements), and mental effort (e.g., pupil dilation) will depend on the specific cognitive processes required by each task. Each task was presented in an ordered

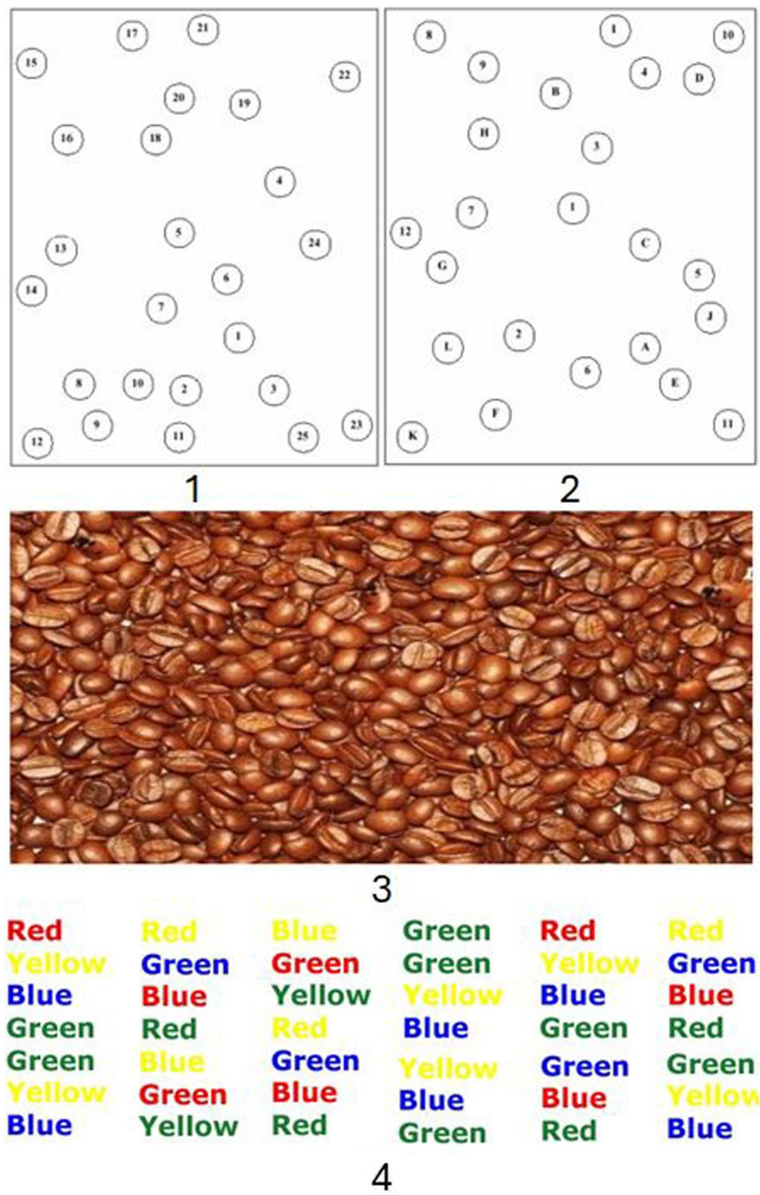

Fig. 1 Visual Stimuli: Trail Making Test (1) TMT-A (2) TMT-B, (3) Visual Sustained Attention Test (VSAT) and (4) Stroop Test

sequence to each participant to minimize the possible order effects. TMT was applied as defined by Llinàs-Reglà et al. [25].

In TMT-A, wearing an eye tracking device, the participants connected the numbers in ascending order with their eyesight. In TMT- B, the circles included both numbers (1 – 13) and letters (A – L); as in Part A, participants were instructed to connect only the circles containing numbers in an ascending pattern, thus neglecting circles containing letters. In VSAT test, participants were asked to detect the relevant target stimulus, three lady bugs, amongst other irrelevant stimuli (coffee beans). The Stroop test required participants to name the color of the ink on a color word when the ink color did not match the word's color.

Results

Twenty participants completed the study. No significant differences were found between the age and gender parameters of the sample population.

Data analysis

In this study, data processing involved several key steps. First, we pre-processed the eye-tracking data by removing outliers and correcting for any calibration errors in the measurements. The analysis of eye-tracking metrics (e.g., gaze duration, fixation count, saccadic movements) was performed using Tobii Pro Lab software, which provides real-time data for these parameters during the cognitive tasks. Descriptive statistics, including means and standard deviations, were calculated for each of the eye-tracking metrics across the tasks. Inferential statistics, including correlation analysis and regression models, were used to assess relationships between eye-tracking metrics, learning styles, and academic performance (GPA) (Table 1). All analyses were conducted using SPSS 24.0 (SPSS, Chicago, IL, USA), with a significance level set at $p < 0.05$.

The participants' visual learning preference scores were calculated, and the visual dimensions (strong, moderate and neutral) were assigned. The eye-tracking metrics for each participant were then aggregated by category, and correlation analyses were conducted to explore the relationship between the learning style dimensions and gaze behaviors (Figs. 2 and 3).

Descriptive statistics

Descriptive statistics were first computed to provide an overview of the participants' characteristics and the distribution of key variables. Table 2 presents the means, standard deviations, and ranges for the key eye-tracking metrics (gaze duration, fixation count, and

Table 1 Correlation and regression analyses of eye-tracking metrics and academic performance

(a) Correlations between fixation duration, fixation count, saccadic movements, pupil diameter, and GPA

Variable 1	Variable 2	Correlation Coefficient	*p*-value
Fixation Duration	Gaze Duration	0.65	0.01
Fixation Count	Saccadic Movements	0.45	0.05
Saccadic Movements	Fixation Duration	0.57	0.02
Pupil Diameter	Gaze Duration	0.72	0.001
GPA	Learning Style (Visual vs. Verbal)	0.38	0.04

(b) The regression analysis assessing the correlation between pupil size and fixation percentage

Variable	Coefficient	Standard Error	t-value	*p*-value
Intercept	0.85	0.12	7.08	0.0001
Pupil Size	0.45	0.09	5	0.001
Fixation Percentage	0.67	0.05	13.4	0.0001

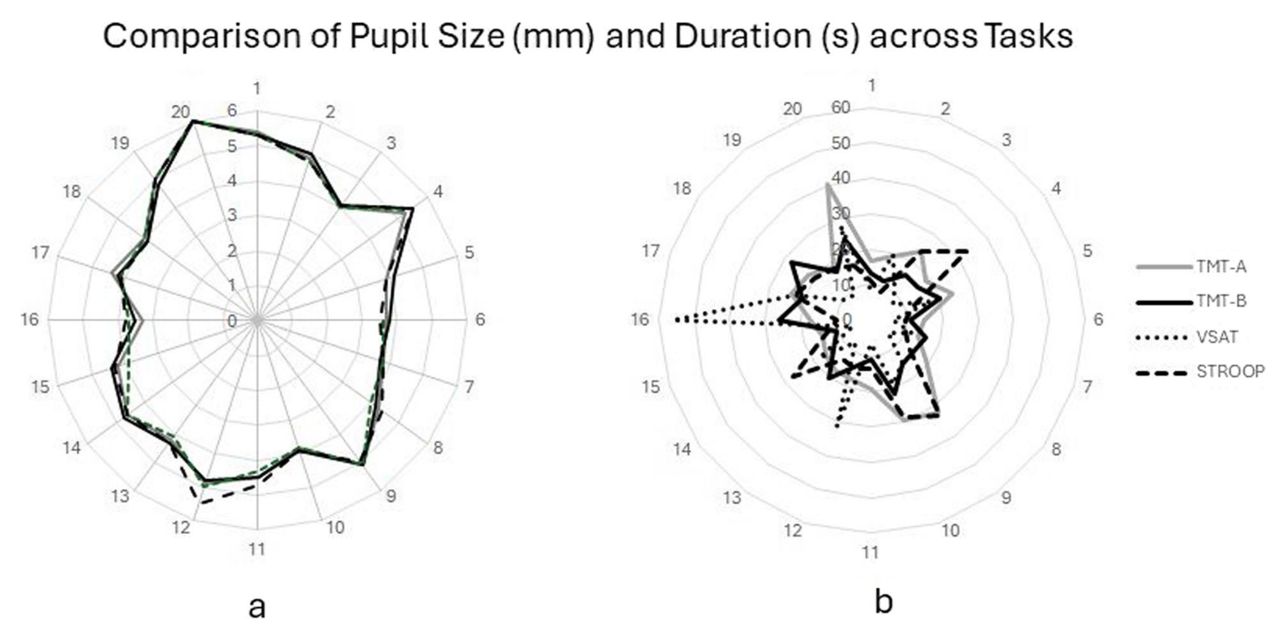

Fig. 2 Comparison of (**a**) Pupil Size (mm) and (**b**) Task Duration (s) across Tasks

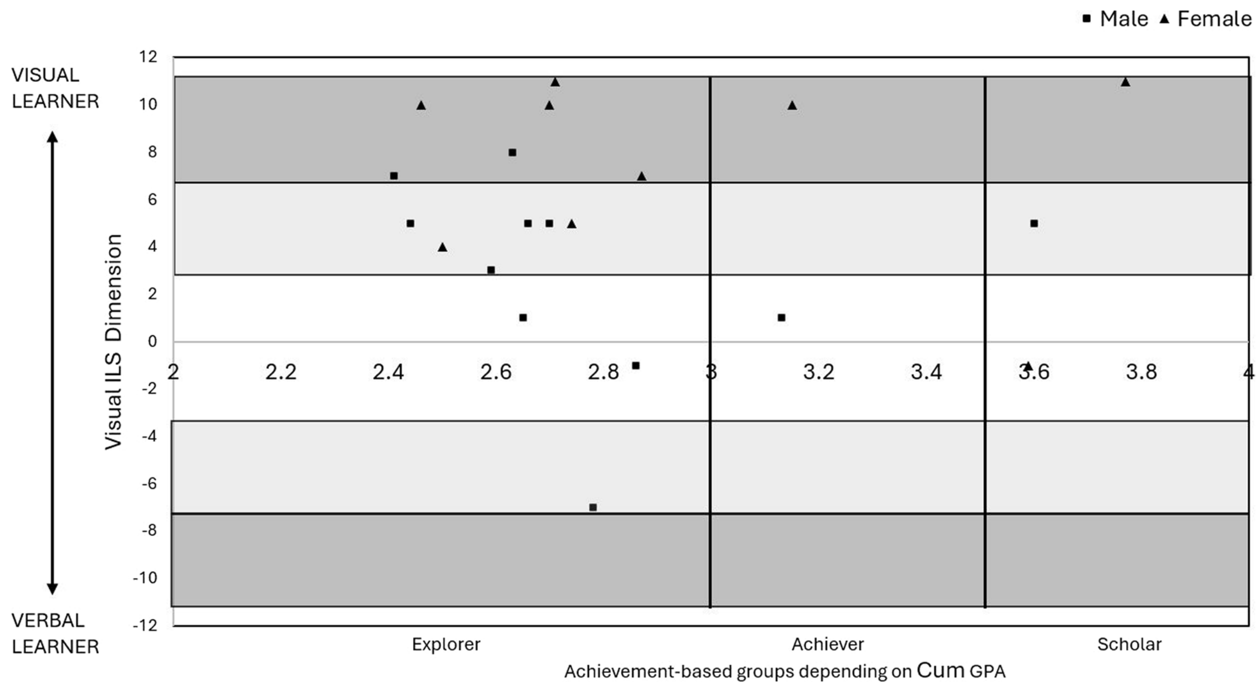

Fig. 3 Achievement based and visual ILS dimension distribution of participants

saccadic movements) across all tasks, as well as for the learning styles and GPA variables.

The average fixation duration across all tasks was 350 ms (SD = 25 ms), with saccadic movements accounting for 6% of the total gaze time. The pupil diameter varied slightly, with an average diameter of 3.2 mm (SD = 0.3 mm). Participants showed a predominant preference for visual learning, with 70% categorized as strong visual learners. The remaining 30% exhibited moderate or verbal preferences. The average GPA of the participants was 3.1 (SD = 0.4), with a range from 2.4 to 3.8.

There was a moderate preference among 33% and a strong preference for visual learning among 56% of the female students, which indicated a right-skewed distribution. None of the female participants had neutral preference (0%) and 1 participant (11%) had verbal learning preference. In contrast, 27% of the male students had neutral, 45% had moderate, and 9% had strong preference for visual learning. Two participants (18%) had verbal learning preference.

The raw eye-tracking data were processed using Tobii Pro Lab (Analyzer Edition). Fixations were defined as any gaze point held for at least 50 ms and saccades were defined as rapid eye movements between fixations. The fixation percentage, average pupil diameter, task duration and number of total eye movement were extracted from the collected data. Average fixation (94%) and saccadic movement (6%) percentages were identical during each task (Fig. 2).

The analysis of pupil diameter and fixation percentage across four cognitive tasks revealed no significant differences in these parameters. The lack of variation in pupil diameter across tasks suggested that the cognitive demands of each test elicited comparable levels of mental effort. The consistency of fixation percentages across the four tasks indicated that participants allocated their visual attention similarly, regardless of the task type (Fig. 3).

Figure 4 illustrated the distribution of participants categorized by their Felder-Soloman Learning Style Index (ILS) dimension on the visual-verbal spectrum, cumulative GPA, and achievement-based groups (Explorer, Achiever, Scholar). Additionally, gender differences were visualized with separate markers for male and female participants. Seventeen participants fell within the visual learning spectrum, particularly in the moderate and strong visual learning ranges (values $\geq +4$). Three participants (1 Female, 2 Male) exhibited verbal learning tendencies (values $\leq$ -4). Female participants dominated the strong visual learner category, particularly in the higher GPA groups (Achiever and Scholar). Male participants were distributed more evenly across the GPA categories but exhibited fewer instances of strong visual preference. In the Explorer group, visual learning preferences were distributed across moderate and strong categories. Among Achievers, participants showed a concentration

Table 2 Participant parameters: Age, Gender, Cum GPA, Groups based on achievement and visual ILS dimension

Participant #	Age	Gender	Cum GPA	Achievement-Based Group	Visual Score	Visual Dimension Group
1	24	M	2.86	Explorer	-1	
2	24	M	2.66	Explorer	5	Moderate
3	25	F	2.7	Explorer	10	Strong
4	24	F	3.77	Scholar	11	Strong
5	25	M	2.44	Explorer	5	moderate
6	25	M	2.78	Explorer	-7	
7	25	F	2.74	Explorer	5	moderate
8	25	M	3.6	Scholar	5	moderate
9	24	M	2.65	Explorer	1	neutral
10	24	F	2.87	Explorer	7	strong
11	25	F	3.59	Scholar	-1	
12	24	M	2.7	Explorer	5	moderate
13	24	F	3.15	Achiever	10	strong
14	25	M	2.59	Explorer	3	moderate
15	24	F	2.5	Explorer	4	moderate
16	24	M	2.41	Explorer	7	strong
17	24	M	3.13	Achiever	1	neutral
18	24	F	2.46	Explorer	10	strong
19	25	F	2.71	Explorer	11	strong
20	25	M	2.63	Explorer	8	moderate

visual-verbal ILS dimension: Neutral: Score: -3 to +3 Moderate: ±5 to ±7 Strong: ±9 to ±11
Achievement-Based Groups Cum GPA: Explorer: (<2.9) Achiever: (3-3.4) Scholar: (3.5-4)
Verbal Learners
Average Cum GPA: 2.85 ± 0.40

in moderate visual learning preference. The Scholar group had fewer participants, predominantly with strong visual learning preference.

Regression analysis results indicated that pupil size and fixation percentage are predictors of cognitive engagement so that both pupil size (coefficient = 0.45) and fixation percentage (coefficient = 0.67) were significant predictors of cognitive engagement, as reflected in the statistical significance (p-values < 0.05) of the model.

Hypothesis testing

Visual Learning Preference and Eye-Tracking Metrics: This hypothesis tested whether the students with strong visual learning preferences exhibit longer fixation durations and more frequent saccadic movements compared to those with verbal or moderate preferences. The results revealed that the visual learners had an average fixation duration of 375 ms (SD = 28 ms), while verbal learners had a shorter average of 320 ms (SD = 20 ms). A one-way ANOVA was conducted to compare fixation durations across learning style groups (strong visual, moderate visual, verbal). The results indicated a significant main effect of learning style on fixation duration, f (2, 18) = 5.32, $p = 0.013$. Post-hoc comparisons using Tukey's HSD test revealed that visual learners had significantly longer fixation durations than verbal learners ($p = 0.04$). No significant differences were found between moderate and strong visual learners ($p = 0.65$).

Visual Learning Preference and Academic Performance: This hypothesis tested whether the visual learners would have higher GPAs compared to verbal learners, particularly among female students. The mean GPA for visual learners was 3.3 (SD = 0.3), while the mean GPA for verbal learners was 2.8 (SD = 0.5). A t-test was conducted to compare GPAs between visual and verbal learners. The results indicated a significant difference in GPA, t (18) = 2.41, $p = 0.026$, with visual learners achieving higher GPAs than verbal learners. Gender differences were examined within each learning style, but no

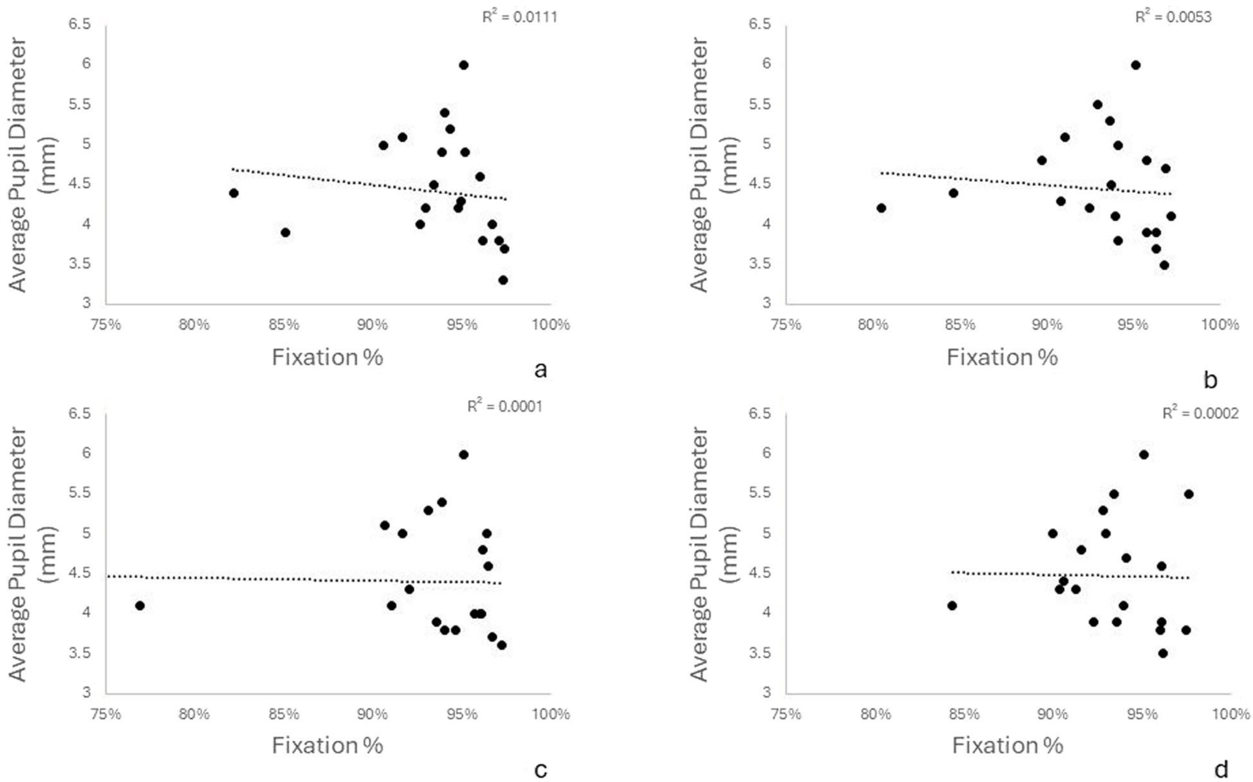

Fig. 4 Comparison of pupil diameter and fixation percentage across four cognitive tasks (**a**) TMT-A, **b** TMT-B, **c** VSAT, and **d** Stroop test

significant interaction between gender and learning style on GPA was found ($p = 0.12$).

Cognitive Load Across Tasks: This hypothesis tested whether the cognitive demands of different tasks would not significantly alter the relationship between learning style and cognitive task performance and the visual learners would show consistent eye-tracking metrics (e.g., fixation percentage) across various tasks, indicating stable cognitive processing strategies. Across tasks, visual learners maintained an average fixation percentage of 94%, with no significant variation across TMT-A, TMT-B, VSAT, and Stroop tests. A repeated-measures ANOVA was conducted to examine the differences in eye-tracking metrics (fixation percentage and pupil diameter) across the four tasks for visual learners. The results showed no significant differences in fixation percentage across tasks, f $(3, 21) = 1.45$, $p = 0.25$, suggesting that the cognitive processing strategies remained consistent across tasks.

Discussion

This study examined the relationship between gaze behavior, learning styles and academic performance among Turkish medicine students, employing eye-tracking technology in conjunction with the Felder-Soloman Index. The analysis focused on metrics including fixation percentage, pupil diameter, and saccadic movements across four cognitive tasks. This approach provided insights into the correlation between visual attention, cognitive effort, and individual learning preferences, as well as their relationship to academic success.

The findings revealed significant gender differences in learning style preferences, with female participants exhibiting strong visual learning tendencies, particularly among those students who achieved higher grades. This is consistent with previous research indicating that female students often prefer visual learning methods, which can enhance their academic performance [26, 27]. In contrast, male participants exhibited greater variability in their learning styles, with a smaller proportion of strong visual learners and a broader distribution across GPA categories. This variability indicates that male students may benefit from a more diverse range of instructional strategies that cater to different learning preferences [28]. According to the information processing model, individuals with a visual learning preference allocate more cognitive resources to visual stimuli, which may manifest in longer gaze durations and more frequent saccadic movements. Previous research has shown that visual learners tend to focus more on visual information, such as diagrams or images, which are observable through eye-tracking metrics [19, 29].

Learning style dimensions, particularly the visual-verbal spectrum, have been linked to academic achievement, with visual learners often performing better in tasks that involve visual or graphical content. Gender differences are also significant, as female students generally exhibit a stronger preference for visual learning, potentially contributing to improved academic performance. The information processing model further suggests that visual learners employ consistent cognitive strategies across different tasks due to the dominance of their visual processing systems. Studies have indicated that visual learners engage similarly with tasks, as evidenced by stable gaze behaviors, such as fixations and saccades, across diverse cognitive challenges. However, research also suggests that while eye-tracking metrics provide valuable insights into attention and cognitive load, they do not always correlate with academic performance, particularly when other factors, such as motivation and study habits, are not considered.

The cognitive tasks employed in the study, such as the Stroop test and the VSAT, serve to illustrate the multifaceted nature of cognitive engagement. The Stroop test is designed to assess executive control and inhibitory control, whereas the VSAT is intended to evaluate sustained attention. This differs from the Trail Making Tests (TMT-A and TMT-B), which are used to evaluate sequential task performance and cognitive flexibility [30–32]. Notwithstanding these differences, the eye-tracking data indicated consistent patterns of visual attention across tasks, with no significant variation in pupil diameter or fixation percentage. This suggests that the cognitive demands of the tasks were uniform [33].

While the eye-tracking data revealed consistent patterns of visual attention across tasks, with no significant variation in pupil diameter or fixation percentage, this uniformity in eye movement patterns should be interpreted with caution. The lack of variation in these metrics suggests that participants allocated similar levels of cognitive resources to each task, indicating a potential uniformity in cognitive load. Specifically, the consistent fixation percentage and similar pupil diameter across tasks may reflect that the participants engaged in comparable cognitive processing, regardless of the differences in task demands. However, this does not necessarily imply that the cognitive demands were identical across all tasks, as the visual attention patterns alone cannot capture the full spectrum of cognitive load. It is important to note that eye-tracking metrics such as gaze duration and saccadic movements are influenced by multiple factors, including task complexity, cognitive strategies, and individual differences in processing. The absence of significant variation in these metrics might indicate that, overall, participants used similar cognitive strategies across the tasks, but this should not automatically be equated with identical cognitive demands. To further clarify the cognitive load imposed by each task, response times and accuracy rates could be added to the data set. These behavioral metrics are essential for understanding how long it took participants to complete each task and how accurate their responses were, offering additional insights into the mental effort required. Longer response times could indicate higher cognitive load or difficulty, while accuracy rates could reveal how well participants managed cognitive resources to perform each task effectively. Including these measures would strengthen the argument and provide a more comprehensive understanding of how cognitive load varies across tasks.

The study's findings indicated a predominant preference for visual learning among students compared to verbal learning styles. This suggests that participants were more inclined to process and retain information through visual means, such as diagrams and images, rather than through verbal methods [33, 34]. This visual dominance highlights the necessity of integrating visually engaging materials into educational strategies to align with the natural learning tendencies of the student cohort. Furthermore, the persistence of this preference for visual learning, irrespective of cumulative GPA, indicates that academic performance does not modify the preferred learning style of the participants [35]. Such insights underscore the necessity for educators to adopt visually enhanced pedagogical approaches to accommodate the predominant preference among students, thereby ensuring inclusivity and efficacy in educational practices [36]. Moreover, the absence of a correlation between GPA and learning style preference indicates that visual learning strategies could be beneficial for students across a wide range of academic performance levels. This reinforces the notion that effective teaching should not be exclusively tailored to high achievers but should also accommodate diverse learning needs [37]. Furthermore, the study revealed that neither GPA nor the dimensions of the Index of Learning Styles (ILS), including visual-verbal preferences, had a significant impact on physiological or behavioral metrics, such as pupil size or task duration. This suggests that the observed patterns in gaze and fixation performance, as well as cognitive task completion times, were not influenced by either academic performance levels or individual learning style preferences [38].

These findings indicate that while learning preferences may vary among students, such preferences and academic achievement levels do not necessarily influence physiological responses, or the time needed to complete tasks. This finding emphasizes the necessity of considering diverse learning strategies without assuming a direct correlation between learning styles, academic performance and physiological or task-based metrics [39]. The study's limitations, including a small sample size of 20 sophomore Turkish Medicine students, indicate that further research is required to enhance the generalizability of the findings. An expansion of the sample size, the inclusion of a wider variety of cognitive tasks and the integration of additional learning style dimensions and eye-tracking metrics would facilitate a more comprehensive understanding of these relationships.

Conclusion

This study explores the relationship between gaze behavior, learning styles, and academic performance among Turkish medical students, using eye-tracking technology and the Felder-Soloman Index of Learning Styles. The findings suggest a predominant preference for visual learning, particularly among female students, and highlight potential links between learning styles and cognitive engagement. However, the observed effect sizes were modest, and further research is needed to confirm whether visually engaging instructional strategies would consistently generate significant improvements in academic performance across diverse student populations.

While the study suggests that visual learners may benefit from visual learning materials, it is important to acknowledge that the influence of learning styles on academic outcomes is complex and may vary depending on other factors, such as cognitive load, task type, and individual preferences. Moreover, gender differences in learning style preferences were evident, with female students showing a stronger preference for visual learning. Therefore, tailoring instructional strategies to consider gender differences may enhance the effectiveness of educational interventions, particularly for female students who demonstrated stronger visual preferences. Given the modest effect sizes observed in this study, we recommend that educators carefully consider the diversity of learning styles within their student populations and adapt their instructional approaches accordingly. Further research with larger sample sizes and a broader range of tasks is necessary to assess the longitudinal consistency of these findings on performance and to refine strategies that can effectively accommodate the diverse needs of students.

Abbreviations

ILS	Felder-Soloman Index of Learning Styles
GPA	Grade Point Average
AOI	Area of Interest
TMT	Trail Making Test
VSAT	Visual Sustained Attention Test
CLT	Cognitive Load Theory
CTML	The Cognitive Theory of Multimedia Learning

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12909-025-06855-y.

Supplementary Material 1.

Authors' contributions

HA, LA and MS contributed to the conception and design of the study. HA conducted the statistical analysis and wrote the initial draft of the manuscript. HA and MS contributed to obtaining the data. All authors contributed to the manuscript revision, read, and approved it for publication.

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None.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

The approval for the study was waived by the local ethics committee of the Institutional Review Board of Acibadem University Scientific Research Ethics Committee (approval number, 2019–7/8). All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed written consent was obtained from all the participants.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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