Eye Movements of Learners with Different Cognitive Styles Watching Digital Learning Videos

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Abstract

In response to the arrival of the post-COVID-19- era, digital learning has become crucial in education. The use of multimedia digital teaching materials in education is becoming increasingly common. Each individual has preferences regarding methods for absorbing information and, in turn, has a distinct learning model. Differences in learners' cognitive styles may be related to their learning performance and their eye movements when browsing information. Therefore, this study explored differences in the eye movements of learners with different cognitive styles (text-based and image-based) while reading graphic information. First, we used the Style of Processing scale to identify learners' cognitive styles. Next, a pretest was administered, and the participants were invited to watch educational videos. Finally, a posttest was conducted. We collected eye movement data while the participants watched the videos, and the collected data were used for subsequent analysis. Examining the use of digital learning materials for different subjects indicated that the participants with image-based cognitive styles focused more on graphic reading than did those with text-based cognitive styles.

Keywords: Cognitive style, Digital learning, Graphic reading, Eye tracking, Learning effectiveness

1 Introduction

The digital learning model has emerged as a major trend in the field of education. Because of recent developments in information technology and the Internet, learning materials have evolved past conventional combinations of text and images to include multimedia digital teaching materials, which are usually presented using computers. Numerous studies have reported that multimedia digital learning materials significantly affect learners' learning effectiveness [1-4]. Compared with text- or image-only materials, multimedia digital learning materials are associated with a lower cognitive load and higher concentration and learning effectiveness [5]. However, if presented in an unsuitable manner, multimedia digital learning materials may distract learners [6], increasing their cognitive load and, in turn, reducing their learning effectiveness. When using digital materials to teach, understanding learners' cognitive styles (text-based or image-based) is crucial [7]. When learners are in a learning environment that aligns with their learning style, they exhibit greater learning performance and information absorption. Learners' preference for multimedia digital learning materials vary with their cognitive styles, and their responses affect the degree to which such materials can facilitate their learning [8]. Therefore, identifying learners' cognitive styles can help researchers provide suitable learning environments and guide learners to achieve more favorable learning outcomes.

In recent years, eye tracking technology has gradually matured. By using eye tracking devices, researcher can directly observe people's eye movements without interfering with their behavior. This method has been widely applied in research on the reading process. Numerous studies have employed eye tracking technology to understand the relationship between text–image configuration and eye movement trajectories [9]. When studying learning materials, different learners exhibit different eye movement patterns and fixate on different points, reflecting the tendency of different individuals to pay attention to different things and process information differently. Therefore, using eye tracking technology is the most direct and most effective method of exploring how learners consume informational materials. By investigating learners' cognitive preferences and reading process, researchers can develop methods for increasing learners' learning effectiveness. To this end, this study explored the eye movement processes of learners with different cognitive styles as they read digital learning materials.

2 Literature Review

2.1 Theories About Cognitive Styles

Cognitive style refers to a learner's learning preferences and habits when they absorb, organize, and process information. Cognitive styles vary because of individual differences and affect the learning methods and strategies learners choose to apply. According to Messick [10], cognitive style refers to the patterns in an individual's processing sequences when they process information or

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experiences. Kozhevnikov [11] defined cognitive style as the stable individual differences people exhibit when handling and organizing information and experiences. Paivio [12] studied the process by which humans receive and process information and proposed that a human's cognitive system consists of two subsystems, namely the verbal and nonverbal subsystems, that are responsible for encoding and storage. These two systems encompass three types of connections: representational connections, referential connections, and associative connections (Figure 1).

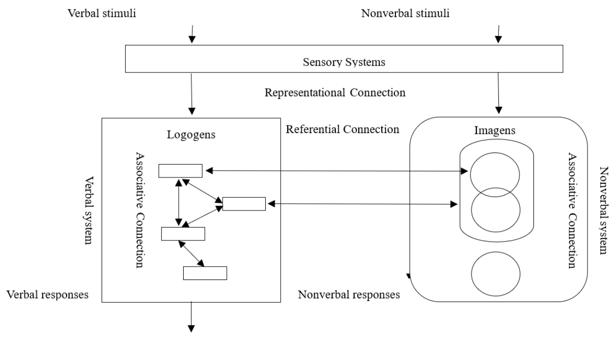


Figure 1. Three connections in Paivio's dual-coding theory

Representational connections are connections between verbal or nonverbal stimuli and representations that are triggered when an individual encounters such stimuli. Representational connections connect corresponding text and image representation systems. Referential connections refer to connections between text and image systems that are formed through cross-referencing. After a referential connection is established, when the brain later receives external stimuli, it will retrieve relevant textual or visual information. Associative connections are connections between elements within the same system with similar characteristics. Several studies have demonstrated that selecting suitable learning materials or learning environments according to learners' cognitive styles can lead to superior learning outcomes [13-14].

This study explored how learners with different cognitive styles process digital learning materials consisting of both text and images. Jonassen [15] maintained that learners have different preferences regarding textual and visual learning materials; some prefer to obtain information by reading text or listening to audio, whereas others prefer to look at images or watch videos or animations. One study demonstrated that when retrieving information, learners with verbal cognitive styles first search in a small area and gradually expand the scope of their search, following a structured reading approach, whereas learners with image-based cognitive styles first perform a broad search of a large area and gradually reduce the scope of their search [16]. The goal of visual cognition education is to enable individuals to focus on the physical forms of objects [17]. Environmental cognition is crucial in every aspect of an individual's life. People's life experiences are rooted in their ability to recognize aspects of their environment and events [18]. Therefore, both reading and information seeking are affected by an individual's cognitive style, which may be text-based or image-based. Previous studies have mostly focused on comparing the learning effectiveness of individuals with different cognitive styles; few have compared the learning processes of such individuals.

On the basis of the literature review, we used the Style of Processing (SOP) scale to assess the participants' cognitive styles and distinguish between image-based and text-based learners. An eye tracking device was used to observe the participants' eye movements as they watched educational videos and compared the eye movement trajectories of participants with different cognitive styles.

2.2 Digital Learning Models

Learning based on digital media is called e-learning. Advancements in digital learning have transformed traditional learning models. By helping students and teachers overcome temporal and spatial limitations, the Internet facilitates the dissemination of knowledge. The Internet provides learners with diverse learning channels. After teachers upload learning materials to digital learning platforms, learners can use them to learn at any time. Bryant et al. [19] discovered that relative to conventional learning methods, digital learning methods are more effective. They can select learning content according to their learning progress. Learners engaging in self-paced independent study must have sufficient self-guided learning abilities and self-awareness. Asynchronous interactive learning refers to a type of digital learning in which the learner and the teacher do not communicate in real time but rather discuss, exchange ideas, and provide feedback through discussion forums or other methods. Synchronous learning is similar to conventional teaching; the teacher teaches learners online in real time and controls the content and pace of learning.

Chen, et al. [20] recognizes seven features of digital learning: no learning obstacles, individualized learning models, reductions in learning costs, multimedia-based learning effectiveness, rich online resources, comprehensive recording of learners' learning progress, and effective accumulation of knowledge. In addition, although conventional teaching is effective in helping students understand concepts, it is less effective in helping students strengthen their thinking abilities. Situational learning activities can be used to integrate various educational techniques and cooperative learning systems into in-class learning, thereby promoting student participation and helping students learn more efficiently [21]. In sum, using multimedia teaching materials can help students learn more efficiently and achieve more favorable learning outcomes.

2.3 Eye Tracking During Reading

Over 80% of the information that humans receive is visual [22], and vision plays a major role in learning and cognition. When people watch videos, their eye movements reflect changes in their cognition; eye movements and psychological reactions are related [23]. People gain knowledge and information through reading, which is a multilayer, multidimensional, and complex mental process that is affected by personal cognition. An individual's eye movements and fixation points during reading are affected by external stimuli and the individual's attention span. Several studies have explored the relationship between eye movements and other cognitive processes [24-27].

When people read, their vision triggers visual perceptions; as they recognize words, they construct knowledge based on and an understanding of what they read through a bottom-up cognitive process [28]. During the reading process, eyes move in short, rapid motions called saccades. They do not move smoothly along with the reading content; rather, they focus briefly on one location and then jump rapidly to the next location [29]. Just and Carpenter [30] maintained that eye movements during reading involve a cyclic interaction between top-down and bottom-up processes, culminating in the reader understanding the meaning of the text.

Eye movements are correlated with attention and willpower and are crucial to visual information processing [31-32]. When people shift their attention, their eyes move [33]. Eye tracking technologies are used to observe, detect, and record eye movements and fixations as an individual processes information. Therefore, they can be used to study the relationships among vision, information processing strategies, and attention. Because eye movement trajectories reflect shifts in individuals' attention, they can be used to identify the areas in which people are most interested or that people deem the most important [34]. By using eye tracking devices to record individuals' eye movement trajectories during reading, researchers can gain insight into people's interpretations of information, cognition, and attention. Therefore, this method can be used to explore effective information presentation models. A major advantage of eye tracking is that it can provide detailed and timely information regarding when and where a person is reading a text [35]. In the field of human-factors engineering and applications, drawing on eye tracking studies, Megaw and Richardson [36] identified nine eye movement observation indicators. Each individual has a distinct reading model. When people read, their eyes move in a series of fixations and saccades. These processes interact with each other and affect reading comprehension. Hannus and Hyona [37] used eye tracking technology to study the eye movements of elementary school students reading science textbooks. Rayner et al. [38] reported similar results. They discovered that although readers spend more time on text and tend to have more fixation points in text areas than in image areas, images are associated with longer fixation durations and saccade lengths. Huang [39] demonstrated that readers with image-based and text-based cognitive styles distribute their attention differently when reading news and that the eye movement trajectories of readers with comprehensive and serial learning styles vary. Hou [40] discovered that field-independent learners outperformed field-dependent learners in terms of learning effectiveness when text and images were simultaneously presented in a multimedia environment.

Overall, images and text have distinct advantages in different fields of study. Although researchers have not determined which medium (images or text) is more conducive to learning, researchers can analyze differences in eye movement sequences, visual attention, and fixation durations to gain insight into readers' cognitive processes. Most relevant studies conducted in Taiwan have used the SOP scale to distinguish between individuals with image-based and text-based cognitive styles. Such studies have also involved experiments conducted using multimedia digital learning materials and the use of eye tracking technology to analyze differences in learners' preferences regarding visual and textual information. Therefore, in this study, we used the SOP scale to classify participants as text-based or image-based learners according to their cognitive styles and used eye tracking devices to observe the participants' eye movements as they watched multimedia educational videos.

3 Methods

3.1 Research Framework

This study explored the effect of cognitive styles on learners' eye movements during reading. We designed educational videos and corresponding test items about chromatics and graphics. As the learners viewed the educational videos, we used eye tracking devices to record their eye movements. We analyzed the eye movement data to determine whether the learners' eye movements were significantly correlated with their cognitive styles. During the experiment, the participants were required to complete a cognitive style test, watch educational videos, and complete a posttest after watching the videos. Figure 2 presents the research framework.

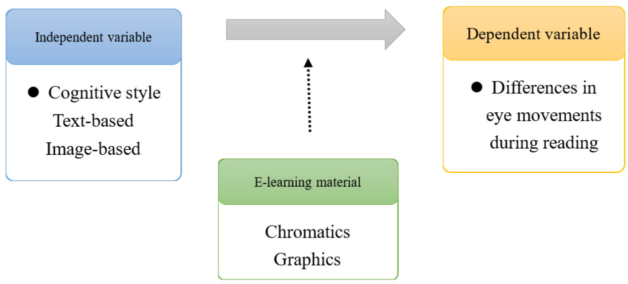


Figure 2. Research framework

We recruited 49 university students from design-related departments. In the first stage, the participants completed the cognitive style test. The SOP scale used in this study was translated by Tzu-Chien Liu [41] and is based on the new version of the SOP scale developed by Heckler, Childers, and Houston [42]. After the experiment was completed, we reviewed the participants' responses and determined that 15 of the participants did not complete all the items on both the pretest and the posttest. The responses of these participants were excluded from our analysis. Of the 34 valid responses, 11 and 23 were from men and women, respectively. In the third stage (the eye movement test), we randomly selected 10 participants and observed their eye movements as they watched the educational videos. Of these participants, five had image-based cognitive styles, and the remaining five had text-based cognitive styles.

3.2 Research Design and Tools

3.2.1 Research Design

The experimental teaching materials were videos about chromatics and graphics, two common subjects on the Visual Communication Design Class B Skill Test. Because first-year students in the department of design are required to enroll in chromatics and graphics courses, the participants in this study had prior knowledge regarding chromatics and graphics. We created slides with text and corresponding images and paired the slides were paired with audio recordings of explanations to create educational videos about chromatics and graphics. In the videos, the text was place on the left or at the top, and the images were placed on the right or at the bottom (Figure 3 and Figure 4). In the instructional videos, the font size of the presented text content is 14 points, and the line spacing is set to 1.5 times the line height. In addition to presenting essential learning content, text, and images, we strive to maintain a clean layout on the page, minimizing any potential factors that may impact the experimental results. The audio explanations focused on the text; the content of the images was mentioned briefly only after the content of the text was explained. To prevent the explanation from affecting the experimental results, we ensured that the explanation did not guide the participants to focus on the images or text nor explicitly state answers to the test questions.

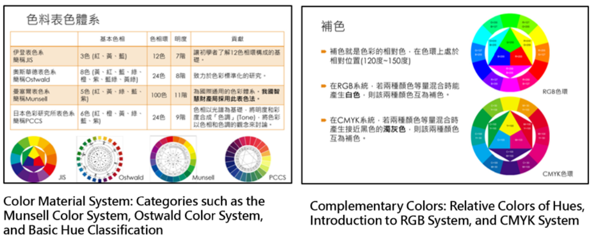


Figure 3. Content and arrangement of text and images in chromatics video

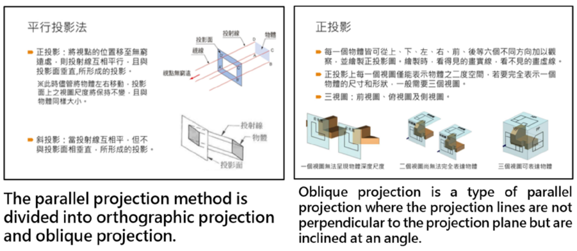
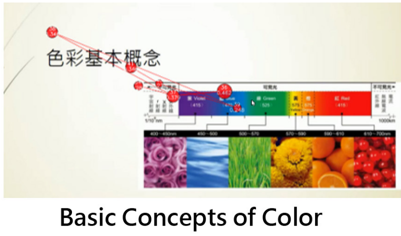
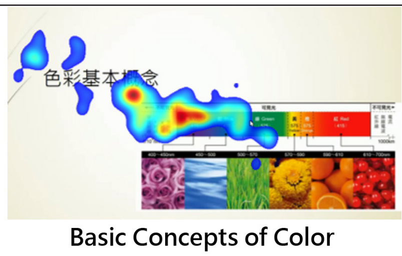
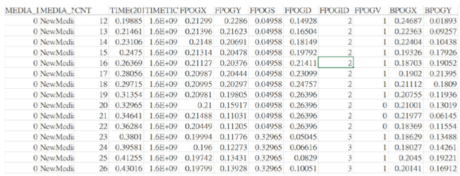


Figure 4. Content and arrangement of text and images in graphics video

3.2.2 Research Tools

The computer was equipped with Gazepoint Analysis eye movement analysis software, which we used to analyze the dynamic area of interest according to the participants' fixation points and durations. We used several icons to represent the areas throughout which the participants' eye movements were distributed. The fixation data (in Excel) and corresponding heat maps and eye movement trajectory graphs were used as the basis for eye movement analysis (Table 1).

Table 1. Eye movement trajectories, heat maps, excel data obtained using gazepoint analysis software

Analysis item	Data of eye movement measurement
Eye movement trajectories	
Heat map analysis	
Excel output of fixation data	

MEDIA_I	MEDIA_N	CNT	TIME(201	TIMETIC	FPOGX	FPOGY	FPOGS	FPOGD	FPOGID	FPOGV	BPOGX	BPOGY
0	NewMedi	12	0.19885	1.6E+09	0.21299	0.2286	0.04958	0.14928	2	1	0.24687	0.01893
0	NewMedi	13	0.21461	1.6E+09	0.21396	0.21623	0.04958	0.16504	2	1	0.22363	0.09257
0	NewMedi	14	0.23106	1.6E+09	0.2148	0.20691	0.04958	0.18149	2	1	0.22404	0.10438
0	NewMedi	15	0.2475	1.6E+09	0.21314	0.20478	0.04958	0.19792	2	1	0.19326	0.17926
0	NewMedi	16	0.26369	1.6E+09	0.21127	0.20376	0.04958	0.21411	2	1	0.18703	0.19052
0	NewMedi	17	0.28056	1.6E+09	0.20987	0.20444	0.04958	0.23099	2	1	0.1902	0.21395
0	NewMedi	18	0.29715	1.6E+09	0.20995	0.20297	0.04958	0.24757	2	1	0.21112	0.1809
0	NewMedi	19	0.31354	1.6E+09	0.20981	0.19805	0.04958	0.26396	2	1	0.20755	0.11936
0	NewMedi	20	0.32965	1.6E+09	0.21	0.15917	0.04958	0.26396	2	0	0.21001	0.13019
0	NewMedi	21	0.34641	1.6E+09	0.21488	0.11031	0.04958	0.26396	2	0	0.21977	0.06145
0	NewMedi	22	0.36284	1.6E+09	0.20449	0.11205	0.04958	0.26396	2	0	0.18369	0.11554
0	NewMedi	23	0.3801	1.6E+09	0.19994	0.11776	0.32965	0.05045	3	1	0.18629	0.13488
0	NewMedi	24	0.39581	1.6E+09	0.196	0.12273	0.32965	0.06616	3	1	0.18027	0.14261
0	NewMedi	25	0.41255	1.6E+09	0.19742	0.13431	0.32965	0.0829	3	1	0.2045	0.19221
0	NewMedi	26	0.43016	1.6E+09	0.19799	0.13928	0.32965	0.10051	3	1	0.20141	0.16912

4 Research Results and Discussion

4.1 Analysis of Learning Effectiveness of Learners with Different Cognitive Styles

We used the new version of the SOP scale to assess the participants' cognitive styles. The scale consists of 20 items, 10 of which measure image processing preferences and 10 of which measure language processing preferences. The scale has high reliability (Cronbach's a = .821). Among the 34 participants who provided valid responses in the first stage, 18 and 16 had image-based and text-based cognitive styles, respectively (Table 2).

Table 2. Cognitive styles of participants

		Sex		Total
		Male	Female	(No. of people)
Cognitive style	Image-based	3	15	18
	Text-based	8	8	16

The pretest and posttest each consisted of 10 items (five related to chromatics and five related to graphics). The participants' scores were statistically analyzed.

4.1.1 Analysis of Learning Effectiveness of All Learners

Our statistical analysis revealed a positive correlation between the content of the educational videos and the learners' scores. However, whether the content of the digital learning videos affected the participants' learning effectiveness required further investigation. Using a dependent-samples t test, we discovered that the participants' mean posttest score (62.35 ± 20.009) was significantly higher than their mean pretest score (mean = 41.47 ± 15.980; $t = -6.026$; $p < .001 < .05$; Table 3), indicating that the videos significantly increased the learners' learning effectiveness.

Table 3. Changes in learner scores

	Mean	N	SD	*t*	*p*
Pretest	41.47	34	15.980	-6.026	.000***
Posttest	62.35	34	20.009		

*** $p<.001$

The pre- and post-tests prepared for this study consist of the same set of questions. However, the design involves swapping the positions of the answers to the questions to prevent learners from answering based on memorization of the answers. The learners' mean scores on the chromatics pretest and posttest were significantly higher than their mean scores on the graphics pretest and posttest, respectively (Table 4). In addition, the learners' mean chromatics and graphics posttest scores were significantly higher than their mean chromatics and graphics pretest scores, respectively (chromatics: $t = -3.880$; $p < .001 < .05$; graphics: $t = -5.022$; $p < .001 < .05$), indicating that the chromatics and graphics contents both significantly increased the learners' learning effectiveness.

Table 4. Learners' scores on chromatics and graphics tests

	Mean	N	SD	*t*	p
Chromatics pretest	24.71	34	12.610	-3.880	.000***
Chromatics posttest	35.00	34	14.196		
Graphics pretest	16.76	34	9.119	-5.022	.000***
Graphics posttest	27.35	34	10.534		

*** $p<0.001$

4.1.2 Analysis of Eye Movements of Learners with Different Cognitive Styles

We used an eye tracking device to record the eye movements of learners with different cognitive styles as they watched the educational videos. Although the all-area mean fixation duration of the text-based learners (0.3338 ± 0.0500 s) was higher than that of image-based learners (0.3267 ± 0.2832 s), the difference was nonsignificant ($t = -0.275$; $p = .790 > .05$; Table 5). The mean number of fixation points of the text-based learners (74.41 ± 9.30) was higher than that of the image-based learners (72.09 ± 5.00), but the difference again was nonsignificant ($t = -0.491$; $p = .636 > .05$). Therefore, the duration and number of fixation points differ nonsignificantly with respect to the cognition styles when watching the digital learning videos.

On the graphics posttest, the image-based learners significantly outperformed the text-based learners. Regarding the eye movement data of the groups (Table 6), when the learners watched the chromatics video, the text-based learners had a longer mean viewing duration and higher mean number of fixation points than did the image-based learners (11.9351 ± 1.6198 vs. 11.1256 ± 0.4043 s and 37.40 ± 3.67 vs. 36.51 ± 3.62, respectively). However, neither the difference in viewing duration ($t = -1.084$; $p = .310 > .05$) nor that in the number of fixation points ($t = -0.387$; $p = .709 > .05$) reached statistical significance. When the learners watched the graphics video, the image-based learners had a longer mean viewing duration and higher mean number of fixation points than did the text-based learners (13.2769 ± 6.5237 vs. 11.9587 ± 2.8174 s and 41.38 ± 14.86 vs. 39.87 ± 6.50, respectively). Similarly, neither the difference in viewing duration ($t = 0.415$; $p = .689 > .05$) nor that in the number of fixation points ($t = 0.212$; $p = .837 > .05$) reached statistical significance. Overall, the cognitive styles of the learners did not significantly affect their viewing duration or number of fixation points while watching the chromatics or graphics videos ($p > .05$).

Table 5. Analysis of eye movements of learners with different cognitive styles watching educational videos

	Cognitive style	N	Mean	SD	F	*t*	*p*
All-area mean fixation duration (s)	Image -based	5	0.3267	0.2832	4.134	-.275	.790
	Text -based	5	0.3338	0.0500			
All-area mean no. of fixation points	Image -based	5	72.09	5.00	1.461	-.491	.636
	Text -based	5	74.41	9.30			

Table 6. Analysis of eye movement trajectories of learners with different cognitive styles while watching videos on different subjects

	Cognitive style	N	Mean	SD	F	*t*	*p*
Chromatics: viewing duration (s)	Image-based	5	11.1256	0.4043	3.128	-1.084	.310
	Text-based	5	11.9351	1.6198			
Chromatics: viewing duration (%)	Image-based	5	35.7636	2.6761	2.094	-.564	.588
	Text-based	5	37.2780	5.3736			
Chromatics: no. of fixation points	Image-based	5	36.51	3.62	0.067	-.387	.709
	Text-based	5	37.40	3.67			
Graphics: viewing duration (s)	Image-based	5	13.2769	6.5237	1.117	.415	.689
	Text-based	5	11.9587	2.8174			
Graphics: viewing duration (%)	Image-based	5	34.1300	11.0856	0.901	-1.173	.275
	Text-based	5	41.115	7.3803			
Graphics: no. of fixation points	Image-based	5	41.38	14.86	1.478	.212	.837
	Text-based	5	39.87	6.50			

4.1.3 Analysis of Eye Movement Trajectories (in Image and Text Areas) of Learners with Different Cognitive Styles

The image-based learners had a longer mean viewing duration and higher mean number of fixation points than did the text-based learners (15.6642 ± 3.8739 vs. 6.8023 ± 3.2029 s and 48.84 ± 9.70 vs. 26.72 ± 14.01, respectively; Table 7). In addition, we identified significant differences in the mean viewing durations ($t = 3.942$; $p = .004 < .05$) and numbers of fixation points (t = 2.902; p = .020 < .05) of the image-based and text-based learners; the image-based learners spent more time focusing on image areas than did the text-based learners. The text-based learners' mean viewing duration of and number of fixation points in the text area were longer and higher, respectively, than those of the image-based learners (16.5166 ± 7.1217 vs. 11.0179 ± 2.8446 s and 51.71 ± 15.85 vs. 41.05 ± 10.17, respectively). However, these differences in viewing duration (t = −1.603; p = .148 > .05) and number of fixation points (t = −1.266; p = .241 > .05) did not reach statistical significance.

Table 7. Statistical data related to fixation on image and text areas

	Cognitive style	N	Mean	SD	F	*t*	*p*
Image area: viewing duration (s)	Image-based	5	15.6642	3.8739	.054	3.942	.004**
	Text-based	5	6.8023	3.2029			
Image area: viewing duration (%)	Image-based	5	41.3840	13.8648	1.718	3.056	.016*
	Text-based	5	18.4460	9.4613			
Image area: no. of fixation points	Image-based	5	48.84	9.70	1.675	2.902	.020*
	Text-based	5	26.72	14.01			
Text area: viewing duration (s)	Image-based	5	11.0179	2.8446	3.303	-1.603	.148
	Text-based	5	16.5166	7.1217			
Text area: viewing duration (%)	Image-based	5	31.8272	9.4849	4.747	-1.242	.249
	Text-based	5	43.7078	19.1754		-	
Text area: no. of fixation points	Image-based	5	41.05	10.17	1.089	-1.266	.241
	Text-based	5	51.71	15.85			

**p*<.05; ** *p*<.01

4.1.4 Analysis of Staring Patterns of Learners with Different Cognitive Styles

Levene's test of homogeneity of variance (Table 8) revealed no significant differences in variance (F = 0.015; p = .906 > .05). Next, we analyzed the differences between image-based and text-based learners with respect to the frequency of which they stared back and forth at the learning materials. The image-based learners had a higher mean number of back-and-forth stares (19.40 ± 4.90) than did the text-based learners (16.30 ± 4.00), but the difference was nonsignificant (t = 1.097; p = .304 > .05; Table 9).

Table 8. Levene's test of homogeneity of variance results

Levene statistic	Degree of freedom 1	Degree of freedom 2	Significance
.015	1	8	.906

Table 9. Numbers of back-and-forth stares between image and text areas

	Cognitive style	N	Mean	S.D.	F	*t*	*p*
No. of stares	Image-based	5	19.40	4.90	.019	1.097	.304
	Text-based	5	16.30	4.00			

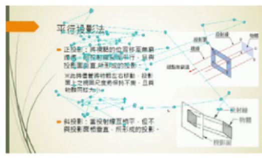
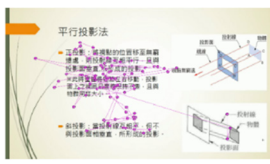
4.2 Analysis of Eye Movement Trajectories of Learners with Different Cognitive Styles During Reading

4.2.1 Eye Movement Trajectories

We used the parts of the chromatics and graphics videos corresponding to the longest audio explanations as examples to compare the eye movement trajectories of learners with different cognitive styles (Table 10).

The participants' mean number of fixation points and concentration of fixation points in the text area were higher than those in the image area (Table 10). The image-based learners had higher numbers of back-and-forth stares between the images and text than did the text-based learners. In addition, the image-based learners had a higher number of fixation points and concentration of fixation points in the image areas and had more scattered eye trajectories than did the text-based learners.

Table 10. Examples of eye movement trajectories of individual learners

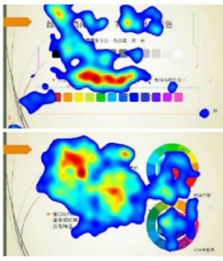
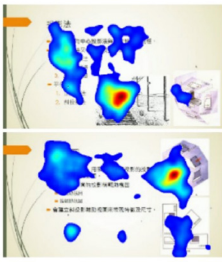
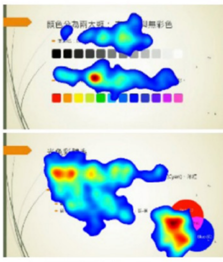
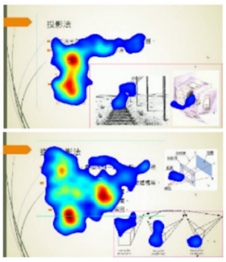
	Chromatics (54 s)	Graphic (47 s)
T1	 Color Systems: Classification into Additive Color Systems and Subtractive Color Systems with Introduction	 Parallel Projection Method: Divided into Orthographic Projection and Oblique Projection
T2	 Color Systems: Classification into Additive Color Systems and Subtractive Color Systems with Introduction	 Parallel Projection Method: Divided into Orthographic Projection and Oblique Projection
W1	 Color Systems: Classification into Additive Color Systems and Subtractive Color Systems with Introduction	 Parallel Projection Method: Divided into Orthographic Projection and Oblique Projection
W2	 Color Systems: Classification into Additive Color Systems and Subtractive Color Systems with Introduction	 Parallel Projection Method: Divided into Orthographic Projection and Oblique Projection

Note. T, image-based learners; W, text-based learners

4.2.2 Eye Tracking Heat Maps

Heat maps were used to visualize the eye movement patterns of learners with different cognitive styles watching digital learning videos. Table 11 presents a heat map in which the dark red areas correspond to the areas on which the learners fixated for extended periods. The participants into image-based and text-based groups according to their cognitive styles, and we overlapped the heat maps of the participants in each group to determine whether the participants in each group spent more time looking at images or text. The heat maps in Table 11 reveal that participants in both groups fixated longer on the text areas than on the image areas. Furthermore, the image-based learners fixated on the image areas longer than did the text-based learners.

Table 11. Eye tracking heat maps of learners with different cognitive styles

	Chromatics	Graphics
Image-based	 Colors are divided into two main categories: chromatic colors and achromatic colors; the color system.	 Projection methods are techniques used to represent three-dimensional objects on a two-dimensional plane.
Text-based	 Colors are divided into two main categories: chromatic colors and achromatic colors; the color system.	 Projection methods are techniques used to represent three-dimensional objects on a two-dimensional plane.

Our statistical analysis of the eye movement data as well as the eye tracking heat maps revealed that overall, the participants spent more time reading the text than looking at the images. This finding is consistent with those of Hannus and Hyona, who reported that learners mostly rely on text to absorb information. In the present study, the differences in the mean fixation durations ($t = -0.275$; $p = .790 > .05$) and mean number of fixation points ($t = -0.491$; $p = .636 > .05$) of participants with different cognitive styles were nonsignificant. Regarding subjects, when watching the chromatics video, the text-based learners had a higher mean fixation duration than did the image-based learners, but when watching the graphics video, the image-based learners had a higher mean fixation duration than did the text-based learners. However, regardless of the subject the participants studied, the differences in the eye movement trajectories of participants with different cognitive styles were nonsignificant.

5 Conclusion

This study was conducted in three stages. First, we used the SOP scale was used to identify learners with different cognitive styles. Next, we used an eye tracking device to explore the characteristics and preferences reflected in the learners' eye movements. Finally, we analyzed the results and drew conclusions accordingly. The results of this study provide insight into the effect of cognitive style on learning effectiveness. Felder and Silverman (1988) study discussed how individuals develop different learning preferences based on their cognitive styles and how understanding these preferences can inform effective teaching strategies. [43] From the data analysis in the aforementioned sections, we can observe that there is no significant difference in learners' pre- and post-test scores based on different learning materials (presentation or slides) styles. We analyzed the participants' pretest and posttest scores and discovered that the digital learning videos effectively helped the participants learn; the participants' cognitive styles did not affect their learning effectiveness. By contrast, the content of the teaching materials did affect the participants' learning effectiveness. The eye tracking experiment (including the heat maps and trajectory graphs) revealed that relative to the text-based learners, the image-based learners paid more attention to the images.

The fixation points of the text-based learners were concentrated in the text areas, and the text-based learners spent more time reading the text than looking at the images. By contrast, the image-based learners tended to have more scattered viewing trajectories and divided their attention between the text areas and the image areas. Overall, both the text-based learners and the image-based learners spent more time looking at the text area than looking at the image area. The participants' cognitive styles affected the time they spent looking at the image area but not the text area. The results of this study support the idea that learners with different cognitive styles have different preferences regarding informational media. The image-based learners had a longer fixation duration and higher number of fixation points in the image areas than did the text-based learners. Although learners with both cognitive styles had longer fixation durations and higher numbers of fixation points in the text areas than in the image areas, no significant between-group differences were identified. Therefore, compared with text-based learners, image-based learners exhibited more notable differences when looking at image information.

This study explored the relationship between cognitive styles and eye movement trajectories during reading. Cognitive styles only affect learners' learning preferences and do not determine their learning effectiveness. Learning preferences affect eye movement trajectories during the consumption of informational media, but this effect was only evident from the data on the participants' fixation on the image areas. Accordingly, we concluded that cognitive style does not affect learning effectiveness; it only affects learners' eye movements when they consume different types of educational media (images or text). The results of this study provide insight into how learners with different cognitive styles consume digital learning materials and may serve as reference in both practical teaching and future research.

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