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RESEARCH ARTICLE

Effects of Attention Level and Learning Style Based on Electroencephalo-Graph Analysis for Learning Behavior in Immersive Virtual Reality

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ABSTRACT Immersive virtual reality technology (IVR) can create contextualized learning environments that learners cannot easily access. It is widely used in education. More and more researchers are paying attention to IVR's influencing factors. However, most of these researches focus on the aspects of technology and environment, ignoring the aspects of learners themselves. Therefore, this paper explores the impact of learners' attention level (AL) and learning style (LS) on learning behavior in IVR. Firstly, the AL data monitored by EEG equipment allows correlation and difference analysis to explore the relationship among AL, LS and learning performance (LP). Then, according to the video-recorded learning behavior data, the lag sequence analysis method is used to analyze the learning behavior sequence transformation of the high-concentration group and low-concentration group so that it can explore the problem learning behaviors of learners with different concentrations. The results show that: in the virtual learning environment (Vir-LE), there is a strong positive correlation between AL and LP. There is no significant difference in LP with different LS, but the AL of visual learners is higher than that of verbal learners. Through this experiment, it is helpful to eliminate the interference factors in the range of human subjective perception and improve the accuracy of the measurement of learning effect.

INDEX TERMS EEG, IVR, LS, learning behavior, lag sequence analysis.

I. INTRODUCTION

IVR is a technology that can generate and perceive the environment of users around them, increase their sense of existence and enable them to experience it. In recent years, it has been widely used to simulate various real learning scenarios [1]. At present, extensive studies have proved the effectiveness of IVR in education [2]. For example, Checa and Bustillo [3] sees IVRs as helping to improve the category of exploratory interactive experiences that can be systematically integrated into standard learning programs; In addition, the program also helps to assess the spatial navigation ability of patients with mild cognitive impairment, and facilitates the education and teaching of special groups [4]. However, there is a little elaboration on how it affects the learning effect. It is necessary to explore the influencing factors to enhance the human experience in IVR and improve LP. Therefore, some scholars began to try to find a connection between the IVR and learners [5]. Petukhov et al. pointed out that most of the existing assessment tools are based on a statistical analysis of subjective tests and questionnaires [6]. Lin et al. thought that the data obtained by personal surveys might lack accuracy because such questionnaires cannot exclude interference factors in the range that can genuinely and objectively reflect human subjective perception [7].

IVR is a particular learning environment. From the perspective of constructivism, an effective learning environment should consider the characteristics of learners because learners' subjective feelings will affect their learning results in the background. Whether in traditional or Vir-LE, LS is the

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critical feature affecting learning results. Therefore, we need to explore the relationship between LS and IVR. In addition, AL has been proven to be a key factor for learning success [8], [9]. Kono pointed out that AL can improve the LP with learning motivation and competitive awareness, but few studies have focused on the relationship between AL and LP in Vir-LE [10].

AL and LS are essential factors that affect the learning results in Vir-LE. However, there are few related types of research, and the existing assessment tools cannot exclude the interference factors within the scope of human subjective perception. Hence, it is necessary to use objective measurement tools. Therefore, an IVR fire safety education game has been designed. The main contributions of this study are:

(1) Firstly, the learning style of learners was measured according to the learning style scale of Soloman&Felder, and then the learners' EEG was acquired by wearable brainwave device during the learning process to collect the attention data of learners. The learning performance was tested through the examination system of the game.

(2) Explore the differences in attention levels and learning effects among learners with different learning styles in immersive virtual reality learning environments.

(3) Record the learning process by means of screen recording to obtain the behavioral data of learners, further explore the relationship between learning behaviors, attention and learning style, and analyze the sequential behavioral patterns of learners with different attention levels

II. LITERATURE REVIEW

A. IVR

Nowadays, IVR has developed rapidly in the world. Because of its substantial flexibility and with the increase of consumer IVR headgear equipment, IVR has an extensive range of applications [11]. Steuer first defined IVR as "the real or simulated environment of perceptual experience simulation," which in turn was described as "experience existing in an environment through communication media" [12]. The term "IVR" is used in the article to distinguish it from other forms of VR; IVR uses head-mounted displays, stereo headphones, and locators to turn off people's perception of reality and provide them with virtual information, thus providing the most vital simulation and improving the sense of immersion. At present, most of the research interests are focused on IVR, which is related to the emergence of consumer IVR devices [13].

Immersive virtual experiment is a process in which learners conduct experimental operation, get familiar with experimental process, obtain experimental data and discover experimental rules through various interactive devices in the virtual environment constructed by immersive virtual reality technology [14]. A large number of researches have explored the advantages of immersive virtual experiments in cultivating skill transfer ability from both theoretical and empirical aspects. Hardie et al. [15] divided the learning environment into four levels according to the similarity and embodied degree with real task scenes. Some scholars also adopt immersive virtual experiments with surround-type helmet-mounted display, which is regarded as a typical representative of highly embodied learning environment. The more embodied learning environment is, the more conducive it is to the occurrence of deep processing and the transfer and application of skills [16]

Existing studies have shown that increasing AL can promote the processing and coding of brain information, thus improving LP [17]. Some studies use self-report tools to measure AL. However, this method is not accurate enough and difficult to operate. Therefore, many studies began to use EEG to observe the change in AL [18]. Previous studies have shown evidence that EEG signals (especially in the βband) contain much information about AL, indicating that it is possible to identify the AL of subjects by studying EEG data [19].

An electroencephalo-graph (EEG) records the process of brain wave activity. In recent years, with the emergence of consumer-grade EEG equipment, more and more researchers began to use portable EEG equipment in research and achieved many research results on education.

B. LEARNING STYLE AND LEARNING PERFORMANCE

The operational behavior in virtual experiment is independent and local, and the deepening of learning makes the operational behavior of single action gradually become the internal descriptive and regular sequence of learning behavior [20]. Researchers gradually begin to pay attention to the mining of learner behavior data in the learning process, and explore the relationship between learning style and learning behavior. Feldman et al. [21] explored the feasibility of using Bayesian network method to mine learning behavior patterns and then predict learning styles, and the results showed that it is highly accurate to predict learning styles by using network learning behavior patterns.

LS describes how learners interact, acquire knowledge and respond to stimuli in the learning environment. At present, many scholars have proven the influence of LS on LP [22]. To achieve a better learning effect, some scholars pointed out that the differences in LS should be considered [23]. Manolis pointed out that LS should be understood to adjust the learning environment and teaching methods to optimize students' learning process [24].

The behavior sequence analysis theory can record the behavior data of qualitative research, then conduct coding analysis and use quantitative statistics to explain the transformation of behavior sequence. In the Vir-LE, learners can take various ways to solve problems, and the order of action taken in the process is considered evidence of LP [25]. Therefore, existing research has focused more on the learning process of learners and found ways to evaluate LP. By recording the learning behavior in the learning process and then using sequential pattern mining to identify the behavior patterns adopted by learners in Vir-LE, this behavior pattern can help designers of Vir-LE to improve the environment design to enhance students' learning efficiency and obtain more process knowledge.

III. RESEARCH METHODS

We explored the influence of learners' attention and learning style on immersive virtual reality learning from two aspects. First, we used correlation analysis and difference analysis to explore the relationship between attention, learning style and learning performance through the attention data monitored by EEG devices. Then, according to the learning behavior data recorded in the video, the lag sequence analysis method was used to analyze the sequence conversion of learning behaviors of learners in the high concentration group and the low concentration group, and to explore the problematic learning behaviors of learners with different concentration levels.

A. PARTICIPANTS AND SETTINGS

The 118 participants in this study were first and second-grade students of the same middle school in Western China. Before the experiment, 326 students were tested on fire safety knowledge and LS. Students with high scores on the test were excluded to reduce the interference to the experiment. In addition, students who had VR experience were excluded. Therefore, the 118 students who finally participated in the experiment had not been exposed to VR before, and their knowledge level of safety and fire protection was average. A participant's data record was ignored because of a problem. Of the 118 participants, 65 were males and 53 were females, aged between 11 and 13. There are 63 students in first grade and 55 in second grade. In this experiment, students use a VR head-mounted display, handheld remote sensing and other virtual devices through a virtual fire safety laboratory for Vir-LE.

B. ENVIRONMENT AND MATERIALS

The experiment was conducted in a closed and quiet classroom with only two researchers and one subject at each time. The equipment used in this experiment includes a computer, Oculus Rift head-mounted display and NeuroSky MindWave brainwave. In addition, we also used screen recording software and an educational game called Fire Safety Lab VR.

MindWave is a kind of biosensor, as shown in Figure 1(a), which is developed by Wuxi Sizhirui Company to collect the brain signals of the experimenters. It is a biosensor that can obtain the participants' concentration and relaxation through the brain wave biological signals. The device has a sensor arm attached to the forehead, ear clip and power controller. The core module of the device is the TGAM module developed by NeuroSky. This module contains a TGAT chip, which can be directly connected with a dry electrode. The EEG electrode (EEG collection point) and REF electrode (reference point) are separated to collect EEG signals and then sent to the module. The op-amp, filter, and ADC processing convert the module into digital signals. After obtaining digital signals, eight groups of independent brainwave data are analyzed internally. They are processing the output Neurosky patented eSense concentration and relaxation index data, and finally output by UART interface.

The Vir-LE for the experiment is composed of Oculus Rift that as shown in Figure 1(b) and IMP studio in Irvine, California, USA, which is a fire safety education game called "Fire Safety Lab VR." The reliability of the Oculus Rift virtual device has been confirmed in previous studies, and it is one of the mainstream devices to provide Vir-LE. The device consists of a head-mounted display, a space sensor and an interactive control handle, which enables participants to interact in the IVR 3D space provided by the device.

Fire Safety Lab VR is an IVR education game developed by IMP studio, as shown in Figure 2. It is used to learn fire safety knowledge and provide theoretical information about fire types, main fire risk factors, etc. The program mainly includes three modules: basic tutorial, learning scene and test scenario. The basic tutorial is used to learn the basic knowledge of VR, such as moving in space and interacting with objects. Four different fire scenarios are simulated in the learning scene to understand the correct operation in the face of varying fire scenarios. The test scenario is used to test the learners' learning achievements. This scenario provides a nonlinear emergency. Learners can use the knowledge of standard programs and make reasonable decisions according to the events. When the learners make the correct decisions, the system will automatically score, giving the test scores at the end of the examination.

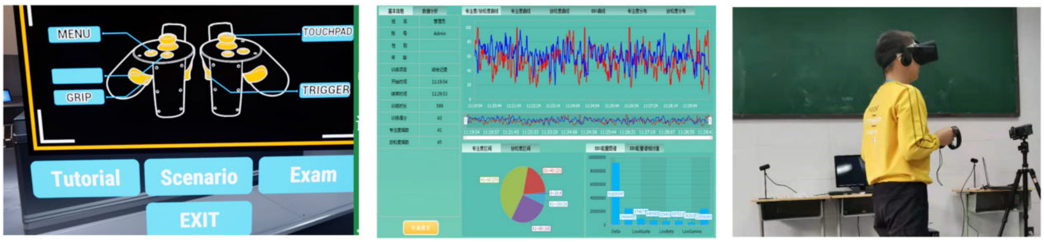
C. MEASURING TOOLS

The fire safety knowledge test and LS test are conducted using a questionnaire survey, and the post-test is carried out through the test scene of the "fire safety laboratory." The fire safety knowledge test aims to evaluate students' fire safety knowledge levels to exclude students with higher fire safety knowledge levels and reduce interference in the experiment. Before the experiment, the reliability and validity of the designed fire safety knowledge questionnaire were pre-tested to ensure reliability and accuracy of the questionnaire. The reliability and validity of the original data were analyzed by SPSS 26.0 software. The coefficient of Cronbach α was $0.82 > 0.8$, the reliability was high, the KMO value was 0.74, and the validity was good. According to the analysis results, the unreasonable items in the questionnaire were revised or deleted—the post-test tests the students' learning achievements in the Vir-LE. Five operations related to fire danger treatment were designed in the fire safety laboratory test scene. Each procedure was correctly completed and 500 points were counted for a successful fire extinguisher. Therefore, the entire score of the post-test link was 750 points. It was converted into a percentage system to facilitate the subsequent data processing.

This paper uses the Felder-Silverman LS Inventory (FLS), which consists of four dimensions: information processing,

(a) MindWave脑波头带设备　　(b) Oculus Rift虚拟设备

FIGURE 1. Screenshot of experimental equipment.



(a) 游戏模式选择界面　　(b) EEG数据采集系统　　(c) 进行实验操作的学生

FIGURE 2. Experimental environment.

perception, input and understanding. Each size contains 11 items to distinguish each LS from two contrasting styles. The four groups of LS are active/contemplative, perceptive/intuitive, visual/verbal, and sequential/comprehensive. FLS has been translated into Chinese, showing acceptable internal consistency and reliability in the 0.51 to 0.64. The reliability coefficient of item response theory (IRT) is between 52 and 84, and the individual reliability coefficient is greater than 50, which is acceptable for Tuckman's attitude or preference assessment [26]. Among the 118 students, 16 were active, 13 were contemplative, 11 were perceptive, 18 were intuitive, 22 were visual, 11 were verbal, 11 were sequential and 14 were comprehensive.

D. CODING FRAMEWORK OF LEARNING BEHAVIOR

To analyze the learners' learning behavior based on Vir-LE, the learning process of learners is recorded by screen recording. The video is qualitatively observed and analyzed by video analysis and content analysis. They combine the 42 behaviors in fire emergencies proposed by Jones et al. [27] and the five basic behavioral models [28] that are effective for fire emergencies determined in Unal's study. A coding scheme is designed to explore students' learning behaviors, as shown in Table 1 for details. Students learning behaviors in Vir-LE are classified into eight types: seeking help, monitoring, thinking, adjusting, testing, searching, irrelevant operations and exploration. ''Seeking help'' includes operation-related problems encountered by learners, such as asking how to move, change position, and grab objects in a virtual laboratory. ''Monitoring'' includes time monitoring and task monitoring. ''Thinking'' refers to the process of thinking independently. ''Adjusting'' is adjusting the position or state of the character in the operation process to complete the corresponding operation. ''Testing'' refers to the correct or wrong operation related to the task, such as pressing the handle of the fire extinguisher to extinguish the fire, broadcasting and making a fire call, etc. ''Searching'' refers to the search for items in completing the task. ''Irrelevant operations'' are actions that are not related to learning tasks, such as grabbing a mouse, chair and other models in a virtual experimental environment. ''Exploration'' refers to the behavior of exploring the objects related to the task and how to use them, such as scouring the use of fire extinguishers, fire masks, etc. All the above behaviors are formulated in a Vir-LE, so using this coding scheme can help to find the correlation between behaviors. To determine the behavior pattern of learners in the Vir-LE, a coder randomly selects ten learners' learning videos for coding. Then the second coder randomly selects 200 pieces of data to encode. To ensure the reliability of the coding scheme, the coding results of the two coders were tested for consistency, and the Kappa was 0.905, indicating good consistency.

E. EXPERIMENTAL PROCESS

The experiment is divided into four parts. Since the simulated fire scene in the virtual environment is in the laboratory, many irrelevant items exist. If the participants do not specify the learning task in advance, they may fail because of distraction. Therefore,

TABLE 1. Behavior code table.

Code	Category	Describe	Example
SH	Seeking help	Operation consultation	Consult on how to grab objects in the environment
MO	Monitoring	Asking about time and task	Ask what the remaining learning tasks are
TH	Thinking	Pause and observe the environment	Stop and look around
AD	Adjusting	Adjust the position or state of a person or object	Adjust the position of fire extinguisher
TE	Testing	Check whether the operation is correct or not	Press the handle of fire extinguisher to put out the fire
SE	Searching	Look for items related to the task	Looking for fire alarm, telephone, etc.
IO	Irrelevant operations	Touching irrelevant objects	Grab water cups, chairs, etc. in the environment
EX	Exploration	The use and use of objects	Explore the use of fire extinguisher, fire mask, etc.

(1) Participants will get a list of tasks to learn about their learning tasks in advance. The learning task involves fire emergency-related operations, including calling the fire alarm, pressing the fire alarm, turning off the power supply, wearing fire masks and gloves, and using a fire extinguisher to extinguish the fire.

(2) In the second step, participants wear an OculusRift device and MindWave headband connected to the computer and then familiarize themselves with the virtual environment in the game of fire safety laboratory, such as using the handle to move and grab things.

(3) After getting familiar with the environment and operation, they formally entered the experiment. In this link, participants had 10 minutes to complete the learning task. At the beginning of the experiment, an HD camera and screen recording software were used to record the experiment process.

(4) Finally, a fire scene is set up in the fire safety game. The participants will have two minutes to extinguish the fire with the knowledge they have learned, and the system will automatically record the score.

IV. RESULTS AND DISCUSSION

Through the above experimental setting, the relationship betwenn LS, AL and LP, as well as differences in behaviro patterns with different will be discussed.

A. THE RELATIONSHIP BETWENN LS, AL AND LP

1) TEST RESULTS

Pearson correlation analysis was used to explore the correlation between AL and LP in Vir-LE. The results were shown in Table 2 that AL and LP had a significant correlation coefficient, R =0.775 ($P = 0.000 < 0.05$). It shows that there is a high correlation between AL and LP. In other words, the higher the AL of learners in the Vir-LE, the higher the LP.

After the experiment, according to the LP data obtained, the data analysis found no significant difference in participants' scores with different LS. Taking information processing LS as an example, an independent sample t-test was conducted on the test scores of active and reflective participants. The results are shown in Table 3 and Table 4. It is assumed that the test scores of active and thoughtful participants are similar, and it can be seen from Table 4 that $t = 0.948$, $P = 0.375 > 0.05$. Accept the null hypothesis that there is no significant difference in the LP of the two types with information processing LS.

At the same time, the data analysis found that the above conclusions were also consistent for the three LS of information input, information perception and information understanding. There was no significant difference in participants' test scores that included those three types, with P values of 0.512, 0.601 and 0.497, respectively.

To explore whether there are differences in the AL with different LS in the Vir-LE, an independent sample T-test was conducted according to the AL and LS of the subjects. The results are shown in Table 5 and Table 6. It can be seen from Table 6 that $t = 2.174$, $P = 0.047 < 0.05$, and there are significant differences in the AL of information input LS (visual and verbal). It can be seen from Table 5 that the average AL of visual learners is 45.65 (standard deviation is 6.578), and that of oral learners is 40.95 (standard deviation is 5.132). The AL of visual learners is higher than that of verbal

TABLE 2. Correlation coefficient matrix of AL and LP.

	AL	LP
LP	.775**	
AL		.775**

**. At 0.01 level (double tail), the correlation was significant.

TABLE 3. Group statistics (active/contemplative LP differences).

LS	Number of cases	Average value	Standard deviation	Mean value of standard error
Active type	16	52.60	36.885	6.799
Contemplative type	13	42.81	36.821	6.752

TABLE 4. Independent sample T test (active/contemplative LP differences).

<table>
<tr><th rowspan="3"></th><th colspan="2">Levin test for variance</th><th colspan="7">Mean value equivalence t test</th></tr>
<tr><th rowspan="2">F</th><th rowspan="2">Significance</th><th rowspan="2">t</th><th rowspan="2">Degrees of freedom</th><th>Sig</th><th rowspan="2">Mean difference</th><th rowspan="2">Standard error difference</th><th colspan="2">95% confidence interval of difference</th></tr>
<tr><th>(double tail)</th><th>lower limit</th><th>upper limit</th></tr>
<tr><td>Assuming equal variance</td><td>0.088</td><td>0.812</td><td>0.948</td><td>27</td><td>0.375</td><td>8.84</td><td>9.421</td><td>-10.543</td><td>27.057</td></tr>
<tr><td>Equal variance is not assumed</td><td></td><td></td><td>0.948</td><td>26.095</td><td>0.375</td><td>8.84</td><td>9.421</td><td>-10.543</td><td>27.057</td></tr>
</table>

learners. In addition, there was no significant difference in AL among the three LS of information processing, information perception and information understanding, with P values of 0.471, 0.427 and 0.822, respectively.

2) ANALYSIS OF TEST RESULTS

According to the results of the data analysis above, it is found that in the Vir-LE, AL and LP are highly positively correlated, which is consistent with the content of other research reports on AL and LP. For example, Yu-ChenKuo found a positive correlation between AL and LP in using brain wave equipment to study the mechanism of AL promotion. Promoting continuous AL can help them improve their LP, especially in the learning environment where students can control their learning progress [29]. The research of Wang et al. found that there was a significant correlation between students' engagement and LP in Vir-LE [30]. In addition to exploring the relationship between AL and LP, the paper is more important to study how to optimize the learning environment and settings of IVR, adjust task strategies, and help learners based on this positive and strong correlation between the two.

Secondly, it is found that LS does not affect their LP in Vir-LE. In a desktop VR or non-immersive VR learning environment, LS has nothing to do with LP. This paper supplements and supports this conclusion from Vir-LE, which is also suitable for learners of various LS.

In addition, when studying the AL with different LS, it is found that visual learners pay more attention than verbal learners. Still, there is no significant difference in LP, which means that visual learners pay more attention than oral learners to achieve the same results. This may be due to the complexity of environment design, which makes visual learners produce more cognitive load. Moreover, from the perspective of LS, visual processing has become a standard learning method for students. The number of visual learners participating in the experiment is twice as much as that of verbal learners. This proportion has reached an astonishing 4.5 times before excluding the subjects in the early stage. This may be because the students were born after 2000 and

TABLE 5. Group staistics (visual/verbal AL difference).

LS	Number of cases	Average value	Standard deviation	Mean value of standard error
Visual type	22	45.65	6.578	1.119
Verbal type	11	40.95	5.132	1.155

TABLE 6. Independent sample T-test(visual/verbal AL difference).

	Levin test for variance		Mean value equivalence t-test						
	F	Significance	t	Degrees of freedom	Sig (double tail)	Mean difference	Standard error difference	95% confidence interval of the difference	
								lower limit	upper limit
Assuming equal variance	1.347	0.299	2.174	31	0.047	3.488	1.725	0.147	6.645
Equal variance is not assumed			2.351	26.074	0.036	3.488	1.654	0.358	6.442

grew up in a digital environment. They are more likely to use visual images for communication, such as pictures or videos taken with their mobile devices, which are more attractive than reading text. However, visual and verbal learners have an average of 41 to 60.

B. DIFFERENCES IN BEHAVIOR PATTERNS WITH DIFFERENT

The fire safety laboratory simulates a real fire scene in which learners must complete self-help and fire-fighting tasks. Previous studies and this study have proved that completing learners' tasks is closely related to the AL they put into the learning process. According to the AL data measured by EEG equipment, the learners were divided into a high-concentration group ($n = 70$) and a low-concentration group ($n = 48$). The lag sequence analysis was carried out with GSEQ5.1 to analyze the behavior sequence of the high AL group and low AL group. GSEQ is a commonly used tool for lag sequence analysis, and the encoded learning behavior is input according to the time sequence. The adjusted residual table can be generated. According to the theory of lag sequence analysis, if Z-score > 1.96, it shows that the behavior path has significance.

1) COMPARISON OF SEQUENTIAL BEHAVIOR PATTERNS IN DIFFERENT CONCENTRATION GROUPS

By using the lag sequence analysis method, output the adjusted residual table of different groups, as shown in Table 7 and Table 8. According to Table 7, in the high-concentration group, "seeking help → thinking," "thinking → searching," "searching → thinking," "thinking → adjusting," "monitoring → thinking," "adjusting → testing," "testing → exploration," "testing →irrelevant operations," "testing→ testing," "exploration → exploration," "exploration → testing" and "irrelevant operations→ irrelevant operations." The Z value of 12 behavior sequences was greater than 1.96, reaching a significant level. As can be seen from Table 8, in the low-concentration group, "seeking help → thinking," "thinking→ seeking help," "thinking → searching," "searching → thinking," "monitoring→ thinking," "thinking → monitoring," "thinking → adjusting," "searching → adjusting," "adjusting → testing," "testing → testing," "testing → monitoring," "testing → thinking," "seeking help → testing," "exploration → irrelevant operations," "exploration → exploration" and "irrelevant operations→ irrelevant operations." The Z value of 16 behavior sequences was greater than 1.96, reaching a significant level. Then, according to these meaningful behavior sequences, the behavior sequence transition diagrams of the high and low groups were drawn, respectively (as shown in Figure 3 and Figure 4). The number on the line between the two behaviors represents Z value, and the thicker the line, the greater the probability of two behaviors appearing successively.

2) ANALYSIS AND DISCUSSION

According to the results presented in Figure 3 and Figure 4, there is a conversion between the same kind of behavior

TABLE 7. Shows the adjusted residual of high concentration group.

	SH	MO	TH	AD	TE	FI	IO	EX
SH	-2.22	-2.1	5.21*	-2.27	1.02	-2.09	-1.39	-0.34
MO	-0.79	-0.08	6.75*	-2.5	-3.53	-0.71	-0.78	-2.14
TH	0.22	1.86	-9.16	7.35	-6.01	11.86*	-3.3	-2.32
AD	-0.67	-3.27	1	-0.42	7.85*	-4.63	-2.77	-0.68
TE	1.73	1.76	-1.35	-3.4	8.97*	-7.1	-0.03	3.57*
FI	-1.22	1.82	9.04*	-0.98	-8.11	-0.12	-2.1	-3.63
IO	-0.61	0.29	-3.06	-2.38	-1.56	-1.4	18.3*	1.11
EX	3.8*	-2.14	-3.24	-2.04	1.52	-2.42	2.64*	8.43*

Note: * indicates that the Z value is significant

TABLE 8. The adjusted residual of low concentration group.

	SH	MO	TH	AD	TE	FI	IO	EX
SH	-1.26	-2.11	5.62*	-3.65	2.28*	-3.54	-0.14	0.90
MO	-1.74	-1.29	8.61*	-2.71	-3.73	0.22	-2.03	-2.35
TH	2.45*	4.57*	-19.71	6.64*	-3.90	19.70*	-3.69	-2.15
AD	-0.73	-4.17	1.66	-3.31	11.55*	-5.34	-2.58	-0.13
TE	1.59	2.23*	3.18*	-0.51	3.61*	-7.91	-2.00	-0.15
FI	-2.23	-0.27	11.55*	4.33*	-9.28	-5.15	-2.71	-3.33
IO	-1.27	-0.33	-1.25	-3.72	-2.60	-1.84	20.95*	0.18
EX	1.58	-1.15	0.40	-4.56	-0.41	-4.37	3.94*	12.00*

Note: * indicates that the Z value is significant

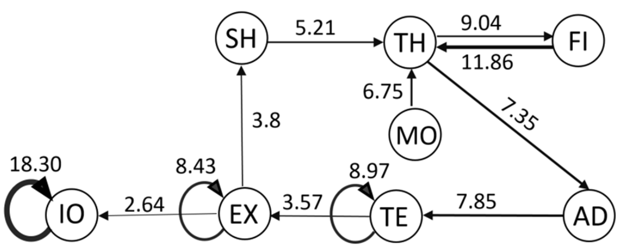


FIGURE 3. Sequence transformation of learning behaviors in high-concentration group.

in the two groups, namely "exploration" → "exploration." The conversion probability of "exploration" behavior in the low-concentration group is higher than in the high-concentration group. The significant learning behavior after transformation is only "irrelevant operations." In addition to "irrelevant operations," there is also "seeking help" behavior after "exploration" behavior in the high concentration group. These learning behavior characteristics indicate that low-concentration learners tend to explore autonomously. Still, their exploration behavior is in a state of dissociation. There is no significant behavior in front of it, so this independent inquiry will likely be blind. It may lead to the distraction of AL and the decrease of the learning effect.

Both the high-concentration group and the low-concentration group had the "EX" → "IO" behavior transition, which indicated that in the learning process, they would be disturbed by some irrelevant environmental factors, so they would be attracted to do some non-task-related actions. More importantly, these unrelated actions were likely to be continuous ("IO" → "IO," Z-score = 20.95, Z-score = 18.30). This means that learners will continue to do a lot of non-learning-related behaviors. The reason may be that the Fire Safety Lab VR used in this paper creates a scene similar to that of a natural laboratory, with complete items and allowing users to interact. Previous studies have shown that presenting too much visual information in Vir-LE can overload learners' cognitive ability, thus damaging the process of selection and organization. At the same time, improper interaction design can also lead to an overload of learners' cognitive and perceptual systems and reduce learning efficiency [31], [32].

Both two groups monitor behavior during the learning process. After the monitoring, they think about allocating time and scheduling tasks to complete all tasks within the specified time. The difference is that low-concentration learners will continue to monitor after thinking ("monitoring" → "thinking," "thinking" → "monitoring"). In addition, the monitoring behavior of low-concentration learners is also

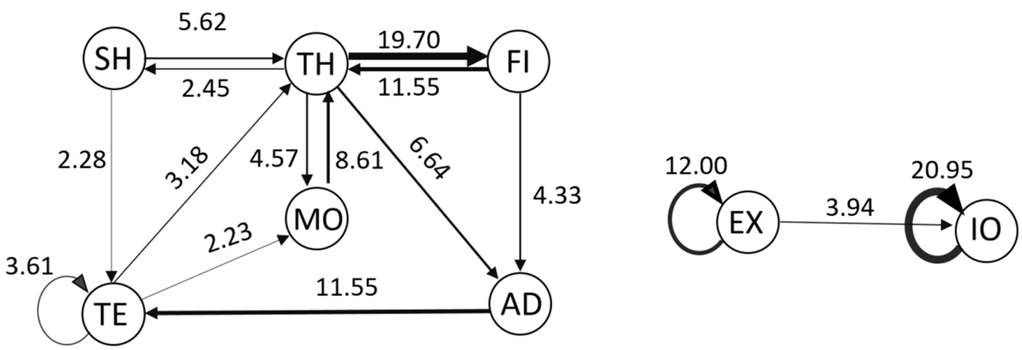


FIGURE 4. Sequence transformation of learning behaviors in a low-concentration group.

shown after "testing" ("testing" → "monitoring"), which indicates that in the process of exploring learning, compared with high-concentration learners, low-concentration learners will continue to monitor after thinking. In other words, learners with low concentration can easily switch to monitoring behavior in thinking and testing. Proper monitoring can help learners complete the learning task. Still, frequent monitoring behavior may cause learners to focus too much on the job and time, thus distracting them from thinking and testing.

The difference between the two groups is also reflected in the "testing" related behavior transformation. Overall, the low-concentration group of learners is more active in the "testing" process. In the low-concentration group, there were five significant behaviors related to "testing," which were: "adjusting" → "testing," "testing" → "testing," "testing" → "monitoring," "testing," → "thinking," "seeking help" → "testing." In the high-concentration group, there were three significant behaviors related to "testing," which were "adjusting," → "testing," "testing," → "testing," "test," → "exploration." Learners with high concentration like to repeat the test or explore independently after the test and then complete the test after thinking and constantly adjusting. While the low concentration learners like to seek help before the test and then repeat the test in the process with monitoring and thinking, it needs to be explained that both seeking help and monitoring are supported by the experimenter, which means that learners need to stop learning in the Vir-LE, and then return to the real environment.

V. CONCLUSION AND SUGGESTIONS

Based on the Vir-LE, this paper uses VR functional games and brain wave equipment to explore the influence of AL and LS on LP. Combined with a large number of behavior data recorded in the game process, innovative integrated behavior pattern analysis and a large amount of brain wave data, it is helpful to explore the characteristics and limitations of Vir-LE. The analysis can provide a preliminary and essential reference for enhancing the system development, educational application and improvement of AL in Vir-LE.

At the same time, improving the AL needs to be fully considered in different types of Vir-LE. According to the results of the other analysis of behavior sequence patterns of high and low-concentration groups, appropriate visual information should be presented in the design of Vir-LE to avoid an overload of cognitive ability caused by too much visual information. In addition, a feedback mechanism can be set up in the learning system. It includes positive and negative feedback, which can reduce the number of times learners get input from outside to enhance their AL in task execution and avoid blind exploration in Vir-LE.

We suggest that future research should be carried out in the following areas. Firstly, with visual processing becoming a standard learning method, the cognitive load and AL of visual learners in Vir-LE deserve further study. Secondly, AL is constantly changing in the process of learning. Pay attention to the change of AL with time and set learning time and knowledge tasks reasonably. Finally, using the eye tracking technology for visual prediction research to optimize visual information presentation, learning scene construction and content design in Vir-LE, so that can further improve AL.

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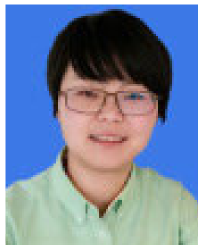

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