On the Personalized Learning Space in Educational Metaverse Based on Heart Rate Signal

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ABSTRACT

The application of the metaverse provides a new perspective for educational innovation and talent training in the new century. By creating multi-channel perceptions such as sight, hearing, and touch through the VR/AR/MR immersive environment, the study found that learners' emotional engagement and cognitive level can be effectively improved in the metaverse. The metaverse integrates information technology, intelligent technology, and digital technology to realize a multimodal human-machine interaction and intelligent evaluation. On this basis, a personalized learning space in the educational metaverse is developed, which is researched by the PPG signal of the learning process, the pre-test, and post-test data to verify each other. In addition, it is verified that learners' learning engagement and learning effects are affected in the personalized learning space of the educational metaverse. A comparison of PPG signal-based metaverse learning and real-world classroom learning is taken.

KEYWORDS

Heart Rate Signal, Metaverse, Personalized Learning Space, Wind Power Generation

INTRODUCTION

China's ministry of education issued A Notice on Supporting Education and Teaching by Informationization on February 6, 2020, during the country's COVID-19 epidemic prevention and control period. According to research, many teachers fail to pay attention to the central position of students during teaching activities. In addition, these teachers do not encourage students to engage in independent activities, deterring the learner from independent exploration due to the pressure of exams (Chen & Yang, 2018). Therefore, a set of multi-dimensional learning spaces must be built that mirror online and offline blended teaching, monitoring the learning process and helping teachers teach and learners learning. The progress of technology also sets a foundation for the development of a personalized learning space in the educational metaverse (PLSEM). In this way, both the integration

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of online and offline education and the advancements in artificial intelligence (AI) pave the way for PLSEM in the post-epidemic period.

Virtual reality (VR), augmented reality (AR), mixed reality (MR), and extended reality (XR) simulate a human's vision, hearing, and touch. These senses enable learners to immerse themselves in a virtual world (Xiaozhe et al., 2018). The *National Medium- and Long-Term Program for Science and Technology Development (2006-2020)* pointed out that VR is one of three cutting-edge technologies in the field of information technology. The white paper on *VR Industry Development 5.0* by the ministry of industry and information technology also affirmed the prospect of the VR industry. The *Educational Informationization 2.0 Action Plan* pointed out that intelligent education will be promoted as a learner-centered intelligent teaching environment is built. In short, it helps to use VR/AR/MR/XR technology to enhance the development of education informationization and modernization in China.

BACKGROUND

The metaverse is not a new concept. It has been described as "wearing headphones and goggles, finding a connected terminal, and entering a virtual space simulated by a computer and paralleled with the real world" (Hyeonju et al., 2022). The metaverse, which extends beyond the universe, is a digital world in which virtual and reality are linked and integrated. In its 2020-2021 Metaverse Development report, the Center for New Media Research defined the metaverse as an internet application based on extended display technology that provides an immersive experience and digital twin technology as it mirrors the real world. Yan et al. (2021) found that a VR immersive environment can be used to promote learners' deep learning of abstract concepts (or continuously promote deep information processing). The University of Warwick confirmed that a VR immersive environment can stimulate learning motivation and promote knowledge internalization, active participation, and other activities (Warren, 2021). Marton and Säaljö (1976) proved that an immersive learning environment can be used to stimulate a positive interest in learning, enabling learners to construct, retain, understand, and internalize knowledge. Research shows that participants' experience in VR is enhanced through its real-world (virtual) environment (Kwon, 2019).

Building an immersive learning environment based on VR/AR/MR/XR technology can encourage learners to participate in learning through exploration. The learning process includes both the physical action, the use of one's brain, and the involvement of emotion, attitudes, and values. Research shows that the metaverse can enhance learning via physical and mental actions (Birt et al., 2018).

The progress of science and technology will continue to strengthen intelligence and digitalization. Data will drive social development and progress. Innovation and reform should also utilize data to help learners through personalized education. Many researchers have combined the biological, cognitive, and developmental sciences to provide a solid foundation for education (Rodriguez, 2012). For example, Daniel and Poole (2009) proposed the concept of the pedagogical ecology.

Nevertheless, at present, empirical research on the evaluation of learners' performance in school or other learning environments is incomplete from the perspective of biological science. The integration of new technologies can study whether learners can learn more deeply via the metaverse. It is necessary to compare learning characteristics, processes, and outcomes between learners' personalized learning in the PLSEM and learning with PPT in a real environment. The PLSEM, which is enhanced through vivid technology, is based on the embodied cognitive theory, cognitive load theory, and cognitive theory of multimedia learning. This article studies whether the PLSEM can promote learning in virtual environments by measuring the physiological index.

RESEARCH PROCESS

Development of the PLSEM

Yunhe (2018) proposed that human living space has extended to a three-dimensional (3D) space made up of physical space, social space, and information space. The emergence of the third-party space coordinates efforts between teaching and learning. This integrated space encompasses both a real learning environment and a virtual learning environment, allowing students to manage themselves within the space according to individual pace and rhythm (Cai, Liu, Wang et al., 2020; Zhiting et al., 2013).

Personal learning space can balance a learner's ability "to learn" and "to love learning" (Guan & Liu, 2013). For example, a wind power farm learning environment is developed using 3D max modeling software to optimize the modeling and render wind power equipment around the farm. The model is imported into Unity 3D to visualize the wind power farm and human-computer interaction of the PLSEM (see Figure 1). OculusQuest2 glasses are used to improve the functionality and interactivity of the system by depicting human-machine interactions as the learner disassembles equipment in the virtual environment and roams around the scene.

According to Cai, Liu, Shen et al. (2020), high-quality learning is achieved through emerging technologies in teaching and activity design, as well as the effective monitoring of learning processes. Therefore, instructional design should be key to the design and development of the PLSEM.

Varela et al. (2016) used the embodied cognitive theory to describe the term "embodied" as cognition that depends on the experience from executing perceived movements. The learner should be placed in an immersive environment created by VR/AR/MR/XR technology. Then, the learner can engage in personalized learning, gaining knowledge through dynamic interactions between the brain, body, and environment as it senses equipment and human-machine interface. Figure 2's virtual wind farm immerses learners in a real-world scenario. In the PLSEM, learners walk into and move around the virtual learning space. The learner can operate a virtual arm to grasp and observe virtual objects.

Based on the cognitive load theory, the learners' external cognitive load is controlled through instructional design in the PLSEM. Their internal cognitive load is controlled by the stimulation of



Figure 1. Development process of the PLSEM

Figure 2. Aerial view of PLSEM



learners' motivation and metacognition (Sweller, 2010). Many empirical studies have confirmed that cognitive load impacts the learning process and learning effects.

Based on the cognitive theory of multimedia learning, Mayer (2014) presented principles of information design in multimedia teaching. These provide an important reference for the design of multimedia learning materials and the development of multimedia teaching practice (Mayer, 2014). Figure 2 shows that learners are attracted to visual impacts via the PLSEM, which is constructed through vivid pictures and text.

Based on Bloom's taxonomy of educational objectives, Figure 3 shows the completion process of the PLSEM's educational objectives. In the PLSEM, the instructional process is centered to complete the instructional objectives. Bloom proposed the cognitive framework of "knowledge, understanding, application, analysis, synthesis, and evaluation" from simple to complex and from concrete to abstract (Nemetz & Bloom, 1957). This theory guides the design of the PLSEM based on Bloom's taxonomy of educational objectives, which is helpful for the learners as they construct knowledge.

Data Detection Based on the MKB0805 Dynamic PPG Heart Rate and Blood Pressure Module

The MKB0805 is a heart rate and blood pressure monitoring device that consists of a YK1801 pulse sensor chip, a HR6707 pulse chip, a HR6816 gain chip, and a SFB9712 algorithm chip. The pulse



Figure 3. Taxonomy of educational objectives of the PLSEM

sensor chip uses the photoelectric volume pulse stroke to sense the human pulse. Then, it extracts the pulse and outputs serial port signals like blood pressure and heart rate through the analog end chip HR607 + HR6816 and the algorithm chip SFB9712.

Figure 4's MKB0805 device can obtain an index for the heart rate and blood pressure. The MKB0805 device identifies pulse wave, electrocardiogram (ECG) waveform output, human wear status recognition, automatic gain, and excellent stability. The smart, wearable blood pressure test module algorithm is inserted into the device to output serial port signals, making data extraction easy and fast. The continuous blood pressure measurement is reliable, precise, stable, and sensitive. It is widely used in heart rate meters, wristbands, bracelets, watches, medical equipment, and fitness equipment. Each periodic contraction and diastolic movement of the heart leads to changes in the blood vessel wall. This produces a pulse wave (Chakraborty et al., 2022). The PPG is a non-invasive method for detecting pulse waves in living tissues by means of photoelectricity testing technology (Alian & Shelley, 2014).

Objects and Procedures of the Experiment

This study included 30 freshmen (with no physical disease) from A University. Participants completed a self-regulated learning ability assessment and transcendental knowledge test questionnaire. Participants were excluded based on significantly high or low scores on self-evaluation and transcendental performance. Finally, 22 people (12 males and 10 females) were selected to participate in the experiment.

Participants were divided into two groups at random. Each participant wore a wristband to measure their heart rate and blood pressure. Group one, which consisted of 11 people, wore VR glasses. Group 2, also made up of 11 people, did not wear VR equipment. A pretest was conducted before the start of the experiment. A post-test was conducted after the experiment. The Workload Profile Index Ratings (WP) scale was used for self-assessment. One group used the PLSEM; the other group used traditional PPT. The level of prior knowledge between the two groups did not show a significant difference (F = 1.252, p = 0.3454 > 0.05).

The teaching content was the utilization coefficient of wind energy in wind power generation (see Figure 5). The study combined the pre- and post-test to analyze the effectiveness of personalized teaching resources in the metaverse as a teaching application.

CONCLUSION

As shown in Table 1, the WP scale measured cognitive load, a new subjective assessment load scale proposed by Tsang and Velazquez (1996). Each of the WP scale's seven items had one question related

Figure 4. MKB0805 dynamic PPG heart module



Figure 5. Experiments with the PLSEM



Table 1. WP scale

Item	Meaning
Central Processing Resources	Psychological resources consumed during task selection and execution
Response Resources	Psychological resources one feels they must consume to react to a task
Space Coding Resources	Psychological resources consumed in the brain's spatial activity during a task
Language Coding Resources	Psychological resources consumed in the brain's language activity during a task
Visual Receiving Resources	Psychological resources consumed to obtain information from the visual channel during a task
Auditory Receiving Resources	Psychological resources consumed to obtain information from the auditory channel during a task
Operating Resources	The impact of operating one's body on the cognitive load during the completion of a task

Source: Tsang and Velazquez (1996)

to learners' information of psychological resource. For example, the question related to item 1 asked, "How much psychological resources did you consume during task selection and execution?" This was measured on an 11-point scale, which ranged from 0 (empty engagement) to 10 (strongly engagement).

Yong (2014) noted that the WP scale is an ideal tool to measure cognitive load in a multimedia environment after the experimental study of multimedia learning. In the WP scale, the control group invested more psychological resources than the experimental group. However, the difference was not obvious in the pre- and post-test. Figure 6 compares the WP data of the two groups. The WP scale of VR group was higher than the PPT group.



Figure 6. Comparison chart of the WP scale of two groups

Physiological parameters refer to some index of body when learner is learning or completing the task. The related index of physiological reaction caused by cognitive load mainly include cardiac activity analysis index, eye activity analysis index and Electro-EncephaloGram (EEG) analysis index (Berntson et al., 1997). Veltman analyzed the physiological index of pilots and found that the heart rate (HR) and the heart rate variability (HRV) were closely related to the cognitive load (Veltman, 2002). Paas and Van Merrienboer (1994) believed that heart rate measurement would not interfere with the learning process. Pass estimated different cognitive load through heart rate changes. The heart rate device was sensitive to subtle changes in cognitive load, which could effectively measure cognitive load. According to the well-known Moens-Korteweg equation, with the blood pressure is increase, the pulse wave propagation is faster, and the pulse wave transmission time is shorter within the same journey. Therefore, the pulse wave transmission time usually has an inverse relationship with the blood pressure (Gribbin et al., 1976). Psychology has a large number of evidences shown that HRV can reflect participants' changes in sustained attention (Berntson et al., 1997). HRV refers to the subtle difference in successive beats. It is resulted from the ability of the autonomic nervous system to regulate the sinus node of the heart. It can reflect the balance and coordination between the autonomic nervous system, sympathetic nervous system, and vagal nervous system (Quintana et al., 2013). Therefore, by analyzing the changes of learners' HR, the vagal tension of the heart can be effectively measured, thus reflecting the self-balance relationship of the nervous system. Currently, HRV has become an important index of the level of attention. High stability of HRV data can sensitively reflect the stability of the learners' attention during the test process (Pendleton et al., 2016).

Figure 7 compared the HR data of the two groups. The chart is drawn by averaging the heart rate data of 11 people in two groups in the same learning time. The HR data are obtained in the experimental group that demonstrated the learners' heart rate fluctuated in the range from 80 to 100 in the PLSEM. While the control group fluctuated between 60 and 80 and tended to be steady. In summary, the experimental group had higher physiological index such as HR and SBP in the PLSEM, which demonstrates the heart beat was accelerated, cardiac output was increased, blood flow speed was accelerated and myocardial oxygen was increased. Therefore, learners' learning emotion and engagement was higher.

The post-test knowledge level questionnaire between the two groups (F = 1.350, p = 0.2971 > 0.05) did not significant difference. Therefore, learning results has little difference through the comparison of pre-test and post-test results, so the author thinks that the learning effects in the process

Figure 7. Heart rate of two groups



Figure 8. Total cognitive load (Seufert et al., 2007)



of learning are equal. Based on the cognitive load theory, cognitive load is related to the specific learning task, and becomes an important influencing factor to solve the problem and construct the schema (Sweller, 1988). Total cognitive load (TCL) is composed of extraneous cognitive load (ECL), intrinsic cognitive load (ICL), and germane cognitive load (GCL). The ECL is caused by teaching activity design or improper learning resource design. The ICL is caused by the learning material and influenced by learners' original knowledge level (Sweller et al., 1998). The GCL is determined by the amount of psychological resources that the learners invest in the schema construction, which promotes learners' learning rather than hindering learning. Because working memory resources occupied by the GCL are mainly used for searching and constructing schema, to improve learning effects (Paas, Renkl et al., 2003). Figure 8 shows the mathematical relationship of the total amount of cognitive load. In this study, in the same situation, only the information input medium is different. The two groups adopted different learning methods. The experimental group adopted the metaverse, while the control group adopted traditional PPT. The wind energy utilization coefficient in wind power generation was used as the same learning content, and teaching objectives designed were the same. Experimental objects had little difference, and teaching activity design of them are same, it can be considered that the ICL is the same. Human cognitive resources are limited, cognitive load always is caused by any learning and problem-solving activity (Paas, Tuovinen et al., 2003). However, according to the WP scale, the experimental group has less psychological input resources, the ECL of experimental group is lower in the PLSEM, when the two groups need to achieve the same learning effects. (Experimental group) ECL (low) < (control group) ECL (high). According to Seufert's classic equation, (Experimental group) ICL (equal) + ECL (low) + GCL (?) = (control group) ICL (equal) + ECL (high) + GCL (?). So (VR group) GCL (high) > (PPT group) GCL (low).

Therefore, the GCL of experimental group is higher than the GCL of control group. The learners' learning effect of experimental group is better. The learning of the experimental group had a promoting effect on the learning effects. Consequently, this research indicates the PLSEM has more visual impact, more personalized design and independent choice, so it can decrease the external cognitive load, and increase the germane cognitive load. The PLSEM makes the learning process more comfortable, more happiness and pleasure.

Intelligent technology, big data, and cloud computing technology in the metaverse make activity monitoring, data acquisition and analysis more convenient and efficient. In addition, data analysis can be used to optimize the learning process by providing appropriate learning support and services. Thus, the PLSEM realizes that personalized learning improves the quality and efficiency of thinking (Zhiting et al., 2016). Research has pointed out that the intelligent learning environment should support learners' personalized learning, lifelong learning, and sustainable development (Chin, 2011).

From the experimental research, it is concluded that the PLSEM can stimulate learners' motivation, improve learning efficiency, and make the learning process more efficient. The PLSEM creates an immersive environment in which personalized learning is constructed for learners. This helps learners cultivate their independent learning ability and improve learning efficiency (Wu et al., 2020). The PLSEM supports teachers and learners. It cultivates learners' abilities and promotes meaningful learning (Akyuz, 2020).

Application Prospects of the PLSEM

The PLSEM promotes a "student-oriented" shift in which learners use digital resources designed according to individual interests and preferences via intelligent components and interactive interfaces. It improves learning efficiency and development. The teaching design supports independent learning.

Personalized learning in the PLSEM is based on intelligent technologies and abstract knowledge. Learning behaviors are digital, optimizing learning paths, planning learning activities, recording the learning process, and evaluating learning results. The PLSEM records learning style, interests, and goals. The PLSEM helps students experience a high-quality virtual environment.

The application of the PLSEM improves the equalization of educational resources. Economic developments have had various impacts on the vast regions within China. Therefore, the allocation of hardware and software resources also differ. With the widespread use of the internet and intelligent terminals, the PLSEM will alleviate the polarization of educational resources. In the PLSEM, PPG signals can record diversified and dynamic data of physiological index in the whole learning process, which can improve learning.

The PLSEM will be used as a new intelligent multimedia learning environment that facilitates the learners' understanding of their learning situation and guides them to achieve a goal of personalized learning (Sun, 2016). With the development of 5G, AI technology, and PPG signals, future evaluation methods will be more accurate, comprehensive, reasonable, and scientific. Learning performance will provide feedback in a timely manner. The PLSEM will benefit personalized learning services like intelligent guidance and learning path optimization. Data analysis based on PPG signals in the PLSEM will intervene in ongoing learning and infer development trends.

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COMPETING INTERESTS

No potential conflict of interest was reported by the authors.

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