pISSN : 2384-2474
eISSN : 2586-7490

RESEARCH ARTICLE

Effects of Metaverse-Based Ecosystem Learning on Knowledge Generation in High School Students: fNIRS Study

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ABSTRACT

The metaverse enables learners to engage in inquiry and interact within virtual spaces, offering high levels of immersion, interactivity, and presence. However, previous studies have primarily focused on affective outcomes, and research on learners' higher-order cognition and knowledge generation remains insufficient. This study examined the effects of metaverse-based ecosystem learning on high school students' biological knowledge generation using functional near-infrared spectroscopy (fNIRS) to measure prefrontal cortex activation. Twenty-seven 11th-grade students at a local high school were participated, with one class assigned to the experimental group (metaverse-based learning, n = 15) and another to the control group (video-based learning, n = 12). During the pretest and posttest, students completed biological knowledge generation tasks while brain activation was recorded. The experimental group showed significantly more activation than the control group in the right dorsolateral prefrontal cortex (DLPFC), frontopolar prefrontal cortex (FP), and bilateral orbitofrontal cortex (OFC), indicating that learners effectively engaged in observation, question, hypothesis, experimental design, and hypothesis evaluation—key processes of knowledge generation—along with heightened cognitive and emotional engagement. These findings support the effectiveness of immersive inquiry-based learning and neuroscientifically informed instructional design and highlight the need to examine generalizability across diverse learning contexts.

Keywords: Metaverse, ecosystem learning, knowledge generation, fNIRS, high school student

OPEN ACCESS

Brain, Digital, & Learning
2025, Vol. 15, No. 4, 555-570
https://doi.org/10.31216/BDL.2025.15.4.2

Received: November 26, 2025
Revised: December 22, 2025
Accepted: December 23, 2025

Introduction

The rapid development of digital technologies has expanded learning environments beyond traditional classroom settings to immersive learning spaces represented by extended reality (XR) and the metaverse (Chamola et al., 2025; Zhang et al., 2022). The metaverse provides an environment in which learners can interact and explore autonomously in a virtual space, offering high levels of immersion, interactivity, and presence (Kye et al., 2021; Onu et al., 2024). These characteristics have been reported to enhance learners' engagement and interest, and especially in science education, they allow learners to engage in highly immersive inquiry activities and experience designing and verifying experiments in virtual environments (Zhang et al., 2022).

Existing studies on metaverse-based learning have primarily focused on affective outcomes such as learners' interest, immersion, and satisfaction (Lee & Kim, 2023; Onu et al., 2024; Yang et al., 2024). However, these affective outcomes alone do not fully address the central goal of science education, which emphasizes learners' ability to generate knowledge through inquiry and explanation. The ultimate goal of science education goes beyond the acquisition of knowledge or affective engagement and lies in enabling learners to generate knowledge by engaging in inquiry, constructing explanations, and reconstructing meaning through conceptual connections (OECD, 2019). For this reason, it is necessary to examine not only the affective effects but also the cognitive changes that occur during metaverse-based science learning. In particular, the high levels of immersion and interactivity provided by the metaverse may support knowledge generation by enabling learners to directly observe phenomena, manipulate variables, and test their own hypotheses. The metaverse can be used to design immersive inquiry-based activities—such as virtual observation, classification, and student-driven investigations—that can substitute outdoor activities and promote learners' knowledge generation processes (E. J. Kim et al., 2024; T. B. Kim et al., 2024).

Knowledge generation in biology learning involves cognitive processes in which learners observe biological phenomena, generate questions and causal explanations, design experimental methods, and test causal explanations following methods (Kwon et al., 2003; Kwon et al., 2011). Specifically, this constitutes a knowledge generation process involving observation, question, hypothesis, experimental design, and hypothesis evaluation (Kwon et al., 2009; Lee et al., 2009b; Lee et al., 2014). This represents a high-level cognitive activity in which learners actively reconstruct meaning and generate new knowledge, rather than merely reproducing information. Such knowledge generation processes are effectively promoted when learners are provided with environments that enable them to pose their own questions and test their hypotheses through diverse inquiry experiences. Accordingly, by supporting learners in directly observing, experimenting, and investigating within an immersive virtual environment, the metaverse has the potential to activate key knowledge generation thinking processes in biology learning.

Previous research on knowledge generation in biology education has primarily relied on external measures such as student reports, questionnaires, and performance assessments (Ariely et al., 2024; Ha et al., 2017). However, these approaches have limitations in capturing the real-time dynamics of learners' thinking processes and the depth of cognitive activity at the neural level. Brain-based measurement technologies can make it possible to compensate for the limitations of scientifically measuring cognitive thinking activities (Kwon et al., 2009). In particular, functional near-infrared spectroscopy (fNIRS) is useful for analyzing learning-related brain activation by measuring changes in oxygenated blood in the prefrontal cortex, enabling the examination of cognitive load, attention, conceptual shifts, transfer, and self-regulation (Fishburn et al., 2014; Kwon et al., 2020; Liu et al., 2024). Through this method, it becomes possible to empirically investigate how metaverse-based ecosystem learning influences learners' thinking processes and cognitive levels.

Therefore, the present study aims to examine the effects of metaverse-based ecosystem learning on high school students' biological knowledge generation. This will be investigated by analyzing changes in brain activation using fNIRS. By integrating immersive ecosystem learning design with neuroscientific measurement, this study seeks to address the existing research gap and provide empirical evidence on whether and how immersion and interactivity in the metaverse facilitate learners' high-level cognitive processes.

Methods

Participants

The participants in this study were 11th-grade students from a local high school, with two classes selected. Of the 30 students who volunteered to participate, data from 27 students were included in the analysis; three students who completed the pretest but did not complete the posttest were excluded. The experimental group comprised 15 students (9 male, 6 female), and the control group consisted of 12 students (7 male, 5 female). All participants took part voluntarily with parental consent and were in good health, without cardiovascular or neurological disorders. According to a handedness test (Oldfield, 1971), all participants were right-handed.

To verify group equivalence prior to the intervention, learning motivation and academic achievement were compared between the two groups. Learning motivation was assessed using a Korean-translated version of Keller's (2009) Course Interest Survey (CIS), which consists of 34 items rated on a 5-point Likert scale. Cronbach's α for all items was .910 for the total sample (experimental: .885; control: .918), indicating good internal consistency (Taber, 2018). Academic achievement was evaluated by the teacher on a four-level scale (high, upper-middle, middle, low) and converted to a 4-point score for analysis. An independent-samples t test and a Mann–Whitney U test were conducted to compare learning motivation and academic achievement between the experimental and control groups, respectively. No significant differences were found in learning motivation, $t(25) = 1.578$, $p = .127$, or academic achievement, $U = 54.000$, $Z = -1.862$, $p = .063$, indicating that the two groups were homogeneous at baseline. Although the groups were comparable at baseline, the relatively small sample size may limit the generalizability of the results.

Research Design

A pretest–posttest control group design was employed to investigate the effects of metaverse-based ecosystem learning on high school students' biological knowledge generation (see Fig. 1). Four class sessions were implemented between the pretest and the posttest, and the instructional content focused on biological knowledge generation activities through ecosystem inquiry. The experimental group engaged in ecosystem inquiry using metaverse platforms (ZEP; Matterport), whereas the control group viewed documentary videos covering the same content. After instruction, both groups completed biological knowledge generation activities using identical worksheets. All sessions were taught by the same teacher.

Brain activation was measured at pretest and posttest while students performed the biological knowledge generation task. Two parallel, non-identical versions of the biological knowledge generation task were administered at pretest and posttest; these versions had been previously validated by three experts who held doctoral degrees in biology education and had research experience in knowledge generation.

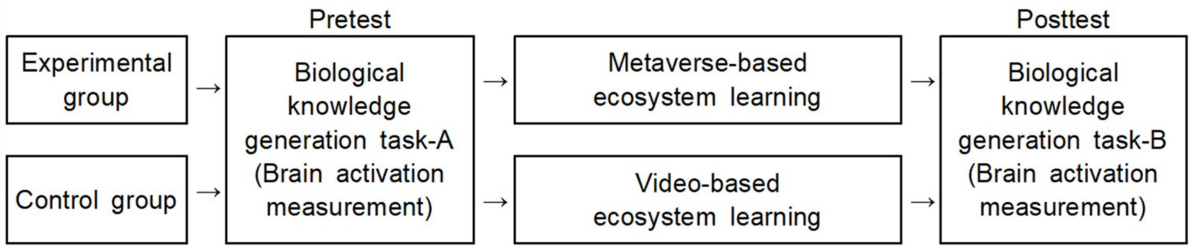

Fig. 1. Research design

Learning Procedures

The metaverse-based ecosystem learning program, which focused on biological knowledge generation through ecosystem inquiry, comprised four class sessions, organized as two linked two-session units that were each implemented twice. In Sessions 1 and 2, students engaged in inquiry and knowledge generation activities related to the Taeanhaean National Park ecosystem, whereas in Sessions 3 and 4, they focused on the Jeju Gotjawal ecosystem (see Table 1).

Taeanhaean National Park is a representative coastal ecosystem characterized by a complex distribution of mudflats, sand dunes, and rocky shores that provide habitats and spawning grounds for diverse marine organisms. The combined effects of tidal dynamics in the mudflats and the transitional sand-dune zone between sea and land contribute to high ecological diversity (E. J. Kim et al., 2024; Koh & Khim, 2014; Yoon et al., 2010). In the experimental condition, students explored a virtual Taeanhaean National Park— including tidal pools, coastal dunes, and wetlands—using the ZEP platform, observing key biological communities and geomorphological features. They were able to change viewpoints, approach or move away from objects, and discuss observations synchronously with peers and the teacher via voice or text chat. In the control condition, students watched documentary videos presenting the same content. The videos included narrated footage, close-up images of representative organisms, panoramic views of landforms, and explanatory captions. Students viewed the videos collectively in the classroom without interactive controls such as navigation, object manipulation, or perspective changes. Afterward, students in both groups engaged in biological knowledge generation activities based on their observations and recorded their findings on worksheets. The biological knowledge generation process included stages such as making observations, generating questions and hypotheses, and designing experiments (including variable selection, manipulation and control methods, and evaluation criteria), with examples provided for guidance. Students first generated biological knowledge individually and then participated in small-group and whole-class discussions and presentations, during which they received feedback from the teacher.

The Jeju Gotjawal is an inland mixed-forest ecosystem formed on irregular lava-based rock formations and characterized by a unique microclimate. Tropical, temperate, and subarctic plant species coexist, and interactions among geology, hydrology, and vegetation create stratified vegetation structures and high biodiversity (Kim et al., 2020; Lee & Kwon, 2019). In the experimental condition, students explored a three-dimensional representation of the Jeju Gotjawal ecosystem using the Matterport platform, which allowed them to navigate the environment, change viewpoints, observe spatial relationships among geological features and vegetation, and interact with peers by posting and responding to comments on selected objects within the virtual environment. In the control condition, students watched documentary videos on the same topic, including narrated explanations, close-up images, and panoramic views, without interactive navigation or perspective control. As in the Taeanhaean National Park sessions, both groups then engaged in biological knowledge generation activities, followed by discussions, presentations, and teacher feedback. Across all sessions, the teacher provided identical learning objectives, guiding prompts, and feedback criteria to both groups to control for teacher-related variables.

Table 1. Learning procedures with contents and activities

Lesson	Contents	Activities	
		Experimental group	Control group
1	Inquiry of the coastal ecosystem in Taeanhaean National Park	Metaverse(ZEP) experience of Taeanhaean National Park	Watching a video about Taeanhaean National Park
2	Biological knowledge generation in the coastal ecosystem of Taeanhaean National Park	Choose one of the subjects experienced in Lesson 1 and complete the activity worksheet	Choose one of the subjects watched in Lesson 1 and complete the activity worksheet
3	Inquiry of the lava forest ecosystem in Jeju Gotjawal	Metaverse(Matterport) experience of Jeju Gotjawal	Watching a video about Jeju Gotjawal
4	Biological knowledge generation in the lava forest ecosystem of Jeju Gotjawal	Choose one of the subjects experienced in Lesson 3 and complete the activity worksheet	Choose one of the subjects watched in Lesson 3 and complete the activity worksheet

Development of Metaverse Contents

In this study, ZEP and Matterport were used as metaverse platforms for the experimental group's ecosystem learning. ZEP (ZEP Co., Ltd.) is a web-based metaverse platform in which avatars move within a two-dimensional virtual space (map) and interact with other avatars and objects. Matterport (Matterport, LLC) is a three-dimensional, photorealistic metaverse platform that creates digital twins of real-world physical spaces through 3D scanning, enabling users to navigate the environment and access embedded multimedia content.

The ZEP-based metaverse environment implemented in this study was an adapted and integrated version of the metaverse spaces developed by Park et al. (2023) and E. J. Kim et al. (2024), designed to model Taeanhaean National Park for ecosystem inquiry (see Fig. 2, left). The Matterport-based metaverse environment was based on Jeju Gotjawal (see Fig. 2, right). To construct this environment, the target site was first surveyed to identify locations that best represented the ecosystem's characteristics. Using a LiDAR-equipped device (iPhone 16 Pro; Apple Inc., 2024) and the Matterport 3D Capture application (version 5.48.1; Matterport, LLC, 2024), the selected locations were scanned to collect spatial data, which were then used to generate a 3D model. Within the resulting 3D space, key biotic and abiotic components of the ecosystem were embedded as text, images, and videos. The Matterport-based metaverse environment was subsequently refined and revised based on expert consultation.

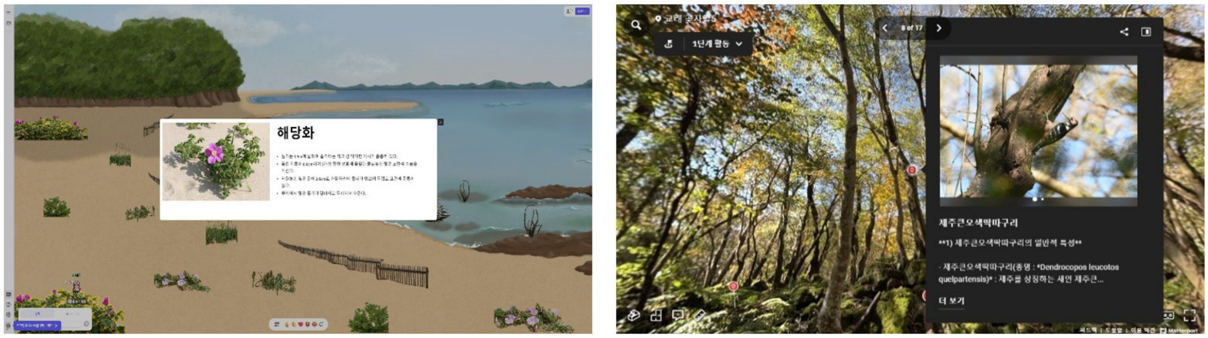

Fig. 2. Metaverse contents developed for the experimental group (left: ZEP; right: Matterport)

Measurement Task of Brain Activation

In this study, a block-design task was developed to measure brain activation during the pretest and posttest (Petersen & Dubis, 2012) and was subsequently revised and refined through pilot testing and expert seminars. The finalized tasks were programmed using E-Prime (version 3.0; Psychology Software Tools, Inc.) to send event markers (e.g., stimulus onset and offset) for synchronization with brain activation data.

As shown in Fig. 3, participants first received standardized instructions outlining key considerations for the measurement session, followed by a resting task that served as the control condition. During the resting task, participants rested with their eyes closed for 60 seconds and then for an additional 60 seconds with their eyes open while fixating on a central cross (+). Subsequently, the biological knowledge generation practice task and the main task were administered. A fixation cross (+) was presented at the center of the screen for 15 seconds before and after each task to allow for signal stabilization.

The biological knowledge generation task was structured as a sequence of cognitive processes involved in generating scientific knowledge: observation, question, hypothesis, experimental design, and hypothesis evaluation. Each subtask began with a 5-second cue indicating the type of thinking required for that segment. This cue was followed by a 30-second presentation of an image depicting a biological phenomenon, during which participants generated biological knowledge corresponding to the cue. The hypothesis segment was allotted 60 seconds, and the hypothesis evaluation segment presented a hypothesis and experimental results rather than an image. Participants then verbally articulated the knowledge they had generated. After completing their verbal response, they clicked the mouse to proceed and then fixated on a cross for 15 seconds before moving on to the next cue.

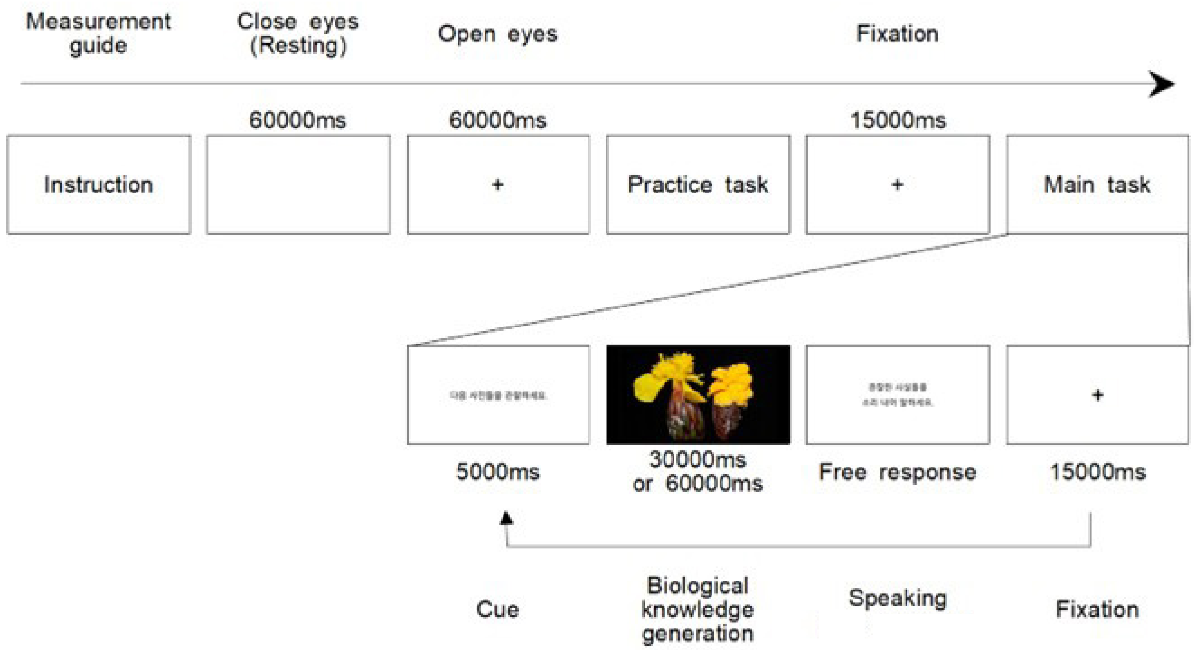

Fig. 3. Task paradigm for measuring brain activation

During expert seminars, the experimental design segment was judged to be too extensive for a single step and was therefore divided into experimental design 1 (identifying variables) and experimental design 2 (designing methods for manipulating and controlling variables and establishing criteria for evaluating the hypothesis). Because participants could not conduct an experiment based on their own design during the hypothesis evaluation segment, materials understanding segment was added. In this segment, participants were presented with researcher-generated materials describing the observation, question, hypothesis, and experimental design. After understanding these materials, they used them in the hypothesis evaluation segment to draw conclusions regarding the hypothesis. Accordingly, the biological knowledge generation task proceeded in the following order: observation, question, hypothesis, experimental design 1, experimental design 2, materials understanding and hypothesis evaluation.

The topics used for the biological knowledge generation tasks were Xyris and pseudoflowers of fungi (pretest task) and symbiosis between springtails and mosses (posttest task), which were selected to ensure equivalent processes and difficulty levels across the pretest and posttest. To verify the equivalence of the two tasks, four in-service secondary-school biology teachers — each holding a master's degree in biology education and having experience in neuroscience research — rated the tasks on difficulty, the extent to which they elicited knowledge generation, and the similarity of the knowledge generation processes using a five-point Likert scale. The mean rating across all items was 4.48 (SD = .35). The item-level content validity index (I-CVI) values ranged from .75 to 1.00, and the scale-level content validity index using the average method (S-CVI/Ave) was .90, indicating satisfactory content equivalence between the two tasks (Lynn, 1986; Polit et al., 2007).

Data Collection

In this study, brain activation was measured using NIRSIT (NS1-H20A, OBELAB Inc.), a headband-type fNIRS device. The measurement area was centered on the prefrontal cortex and included the left and right ventrolateral prefrontal cortex (VLPFC), dorsolateral prefrontal cortex (DLPFC), frontopolar prefrontal cortex (FP), and orbitofrontal cortex (OFC), using a total of 48 channels (OBELAB Inc., 2023). The device emits near-infrared light at wavelengths of 780 nm and 850 nm from 24 sources and measures the intensity of the returning light at 32 detectors to calculate real-time changes in cerebral oxygenation. The distance between each source and detector was 3 cm, and the sampling rate was 8.138 Hz.

The primary data in this study were the brain activation signals collected using the NIRSIT device. Data collection was conducted with the NIRSIT device and its proprietary data acquisition software, NIRSIT Eye PC Tool (version 2.8.2; OBELAB Inc.). Measurements were conducted within the educational institution to which each participant belonged, in a quiet room with controllable lighting and minimal external distraction. Participants were seated upright in a chair, and the laptop monitor used to present the tasks was adjusted to each participant's eye level. During task performance, participants operated a mouse with their right hand, and the distance between the monitor and the participant was adjusted to ensure a comfortable posture. To minimize motion artifacts, participants were instructed to remain as still as possible.

The researcher sat beside each participant, provided instructions regarding measurement procedures and precautions, assisted with positioning and fitting the NIRSIT device, and continuously monitored data acquisition and real-time recording. The researcher also recorded participants' verbalizations during task performance and responded to any questions or noted any unusual behaviors. The measurement laptop and audio-recording device were placed outside the participant's direct line of sight.

Data Analysis

To analyze the brain activation data collected in this study, we used the NIRSIT Analysis Tool (version 3.8.4; OBELAB Inc.). First, markers corresponding to the resting period (control task block) and the biological knowledge generation period (experimental task block) were selected from the raw data obtained during the pretest and posttest tasks, and task numbers were assigned accordingly. The resting period consisted of a task in which participants closed their eyes and relaxed, whereas the biological knowledge generation period comprised tasks requiring the generation of observation, question, hypothesis, experimental design, and hypothesis evaluation knowledge.

For preprocessing, a high-pass filter (discrete cosine transform [DCT], 0.005 Hz) and a low-pass filter (DCT, 0.01 Hz) were applied to remove physiological noise such as respiration and heart rate, as well as motion artifacts. The signal-to-noise ratio (SNR) threshold for all channels was set to 20 dB, and channels that did not meet this threshold were excluded from further analysis. The three-quarters point of the resting period was used as the baseline to calculate changes in optical density, which were then converted into changes in oxyhemoglobin concentration using the modified Beer–Lambert law (MBLL; Delpy et al., 1988).

To estimate brain activation elicited during the biological knowledge generation tasks, we applied a general linear model (GLM) to each channel. Brain activation for each channel was quantified as the regression coefficient (β), calculated by subtracting the resting period from the biological knowledge generation period. Pretest–posttest changes in brain activation within each group were analyzed using paired-samples t tests on the regression coefficients (β), with the significance level set at $p < .05$. Differences between the experimental and control groups were examined using independent-samples t tests on changes in regression coefficients ($\Delta\beta = \beta_{post} - \beta_{pre}$) in IBM SPSS Statistics (version 22.0; IBM Corp., 2013), with the significance level set at $p < .05$. The magnitude of the observed effects was quantified using effect sizes. Within-group pretest–posttest effect sizes were estimated using Cohen's d_z ($d_z = t/\sqrt{n}$; Cohen, 1988). Between-group differences in change scores were quantified using Hedges' g, a bias-corrected effect size for independent samples with small sample sizes (Hedges & Olkin, 1985). Finally, BrainNet Viewer (version 1.7; Xia et al., 2013) was used to visualize only those channels that showed significant effects, highlighting their anatomical locations in the brain.

Results and Discussions

Analysis of Brain Activation Changes between Pretest and Posttest

As shown in Table 2 and Fig. 4(a), the within-group analysis of the pretest and posttest data suggested that the experimental group showed a significant increase in brain activation after metaverse-based ecosystem learning relative to the pretest ($p < .05$). Significant activation was primarily observed in the bilateral DLPFC, FP, and OFC. Specifically, significant changes were found in channel 3 (right DLPFC, Brodmann area [BA] 9), channel 6 (right DLPFC, BA 46), and channels 11, 17, 18, 19, 20, and 43 (bilateral DLPFC, BA 10). Additional significant activation was observed in channels 7, 8, 23, 24, 25, 26, 27, 28, and 36 (bilateral FP, BA 10) and in channels 29 and 31 (bilateral OFC, BA 11). Brain activation maps were visualized with a threshold corresponding to $t > 1.692$, consistent with the color scale range (1.692–4.454) shown in Fig. 4(a). The within-group effect sizes, calculated as Cohen's d_z, suggested moderate effects across the significant channels ($d_z = .43–.76$; Cohen, 1988). In contrast, the control group did not show a significant difference between the pretest and posttest ($p > .05$).

The significant increase in brain activation observed in the experimental group suggests that metaverse-based ecosystem learning may be associated with learners' biological knowledge generation. The left DLPFC is associated with verbal working memory, logical thinking, and analytical planning (Hertrich et al., 2021; Schmidt et al., 2018) and has been shown to be activated throughout the entire biological knowledge generation process—including observation, question, hypothesis, experimental design, and hypothesis evaluation (Kwon et al., 2007; Kwon et al., 2009; Lee et al., 2009a; Lee et al., 2009b; Lee et al., 2014). This pattern may indicate that the logical and analytical thinking based on verbal working-memory information processing required for biological knowledge generation was more strongly engaged than at pretest. The right DLPFC, which is involved in visuospatial reasoning, causal problem-solving, and attentional control (Smith & Jonides, 1999), is also engaged during comprehension and working-memory-based inferential reasoning (Lee & Kwon, 2012). Its activation in the experimental group may reflect greater engagement of reasoning and attentional processes in the metaverse learning environment.

The FP is implicated in goal-directed cognition and the regulation of multitasking (Burgess et al., 2007; Koechlin et al., 1999). It is particularly engaged when learners integrate new information, maintain long-term plans, and adjust strategies in response to changing rules (Koechlin & Hyafil, 2007; Strange et al., 2001). The increased FP activation observed in the experimental group may suggest that learners were more engaged in organizing information and conducting strategic inquiry aligned with their learning objectives.

The OFC, associated with reward processing, immersion, positive emotion, and learning motivation (Ballesta et al., 2020; Murphy et al., 2003), when co-activated with the FP, may have contributed to goal-directed thinking and planning from an emotional and motivational perspective (Kwon et al., 2020). This co-activation pattern may suggest that OFC was associated with learners' active engagement in goal-directed thinking and planning during the biological knowledge generation process. Overall, metaverse-based ecosystem learning appears to be associated with the coordinated engagement of cognitive, emotional, and motivational processes, thereby potentially supporting learners' biological knowledge generation.

Table 2. Channels showing significant brain activation changes between the pretest and posttest in the experimental group ($p < .05$)

Region	BA	Hemisphere	Channel	t	Cohen's d_z
DLPFC	9	R	3	2.386	.46
	10	R	11	3.282	.63
			17	2.565	.49
			18	2.578	.50
		L	19	2.728	.53
			20	2.726	.52
			43	2.502	.48
	46	R	6	3.148	.61
FP	10	R	7	3.056	.59
			8	2.224	.43
			25	3.009	.58
			26	3.936	.76
		L	23	3.200	.62
			24	2.820	.54
			27	2.955	.57
			28	2.210	.43
			36	3.121	.60
OFC	11	R	29	2.887	.56
		L	31	3.127	.60

DLPFC: dorsolateral prefrontal cortex, FP: frontopolar prefrontal cortex, OFC: orbitofrontal cortex, BA: Brodmann area, R: right hemisphere, L: left hemisphere

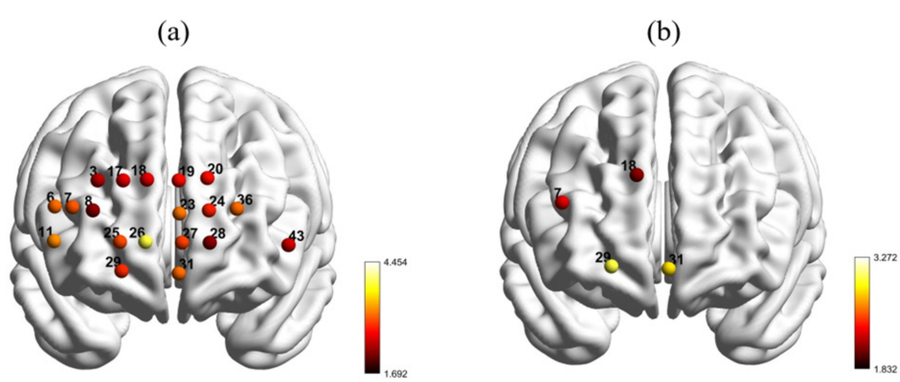

Fig. 4. Visualization of significant brain activation changes ($p < .05$): (a) Brain activation changes between the pretest and posttest in the experimental group, (b) Differences in brain activation changes between the experimental and control groups

Comparison of Brain Activation Changes Between Experimental and Control Groups

To examine whether metaverse-based ecosystem learning was associated with greater biological knowledge generation than video-based learning, we analyzed between-group differences in brain activation. As shown in Table 3 and Fig. 4(b), statistically significant differences were observed between the experimental and control groups. Specifically, the experimental group showed significantly greater activation than the control group in channel 18 (right DLPFC, BA 10), channel 7 (right FP, BA 10), and channels 29 and 31 (bilateral OFC, BA 11), all $p < .05$. Brain activation maps were visualized with a threshold corresponding to $t > 1.832$, consistent with the color scale range (1.832–3.272) shown in Fig. 4(b). Between-group effect sizes, calculated as Hedges' g, suggested moderate to large effects for these channels (g = .79–1.13; Hedges & Olkin, 1985). These results suggest greater brain activation in the experimental group under the conditions examined.

Table 3. Channels showing significant differences in brain activation changes between the experimental and control groups ($p < .05$)

Region	BA	Hemisphere	Channel	t	Hedges' g
DLPFC	10	R	18	2.102	.79
FP	10	R	7	2.294	.86
OFC	11	R	29	3.002	1.13
		L	31	2.832	1.06

DLPFC: dorsolateral prefrontal cortex, FP: frontopolar prefrontal cortex, OFC: orbitofrontal cortex, BA: Brodmann area, R: right hemisphere, L: left hemisphere

These findings suggest that metaverse-based ecosystem learning may be associated with learners' biological knowledge generation compared to video-based learning. In particular, increased activation in the right DLPFC may suggest that learners were more engaged in visuospatial reasoning, causal problem-solving, and sustained attentional focus, potentially reflecting experiences of active reasoning and problem-solving based on information presented in an immersive virtual environment (Kaplan et al., 2016). Given that the pretest and posttest tasks were identical, this pattern may reflect enhanced germane cognitive load (Sweller, 2010). Learners may have allocated more cognitive resources to learning-related processes, such as organizing information, applying strategies, and adapting to problem-solving demands. These effects may not be solely explained by task difficulty or extraneous load.

Additionally, heightened activation in the right FP may reflect learners' processes of setting inquiry goals, predicting subsequent steps in exploration, and self-regulating their learning (Koechlin, 2011). Concurrently, increased activation in the bilateral OFC may indicate that features of the metaverse environment—such as real-time interaction, a strong sense of visual presence, and virtual reward systems—were associated with learners' positive emotions and sense of immersion (E. J. Kim et al., 2024; T. B. Kim et al., 2024; Rolls et al., 2020).

However, it should be noted that increased brain activation does not directly imply improved behavioral performance. Higher activation may reflect greater cognitive effort, compensatory processing, or heightened attentional engagement rather than a one-to-one enhancement in learning outcomes (Ayaz et al., 2012). Overall, students successfully engaged in the full biological knowledge generation process—including observation, question, hypothesis, experimental design, and hypothesis evaluation—though individual differences were observed in the completeness and depth of their outputs. Nevertheless, this pattern still provides evidence supporting the cognitive and affective value of metaverse-based ecosystem learning, even though increased brain activation does not uniformly translate into higher levels of knowledge generation.

Meanwhile, although the left DLPFC and left FP showed increased activation in pretest–posttest comparisons, no significant between-group differences were observed. This pattern may reflect that both groups engaged in biological knowledge generation activities involving verbal explanation and logical understanding, thereby commonly recruiting left prefrontal cognitive processes (Schmidt et al., 2018; Toepper et al., 2010). Overall, metaverse-based learning appears to provide a cognitively and affectively integrated learning experience that extends beyond the primarily left-prefrontal, language- and logic-based processes targeted by conventional video-based learning. By simultaneously engaging right prefrontal regions implicated in spatial reasoning, self-regulated inquiry, and emotional immersion, metaverse-based learning may support both higher-order cognitive control and affective engagement beyond simple information comprehension.

Conclusions and Implications

This study used fNIRS to examine the effects of metaverse-based ecosystem learning on high school students' generation of biological knowledge. The following conclusions were drawn.

First, in the experimental group that engaged in metaverse-based ecosystem learning, activation across prefrontal regions—including the bilateral DLPFC, FP, and OFC—significantly increased from pretest to posttest. These results suggest that, within the context of this study, learners were simultaneously engaged in logical and analytical thinking, visuospatial reasoning, self-regulated inquiry, goal-directed planning, and emotionally driven engagement guided by motivational and reward-related processes. In other words, the metaverse environment appears to be associated with the engagement of higher-order cognitive functions alongside related affective and motivational processes.

Second, compared to the control group that participated in video-based learning, the experimental group exhibited greater changes in activation in the right DLPFC, FP, and bilateral OFC. This pattern suggests that, under the specific instructional conditions examined, metaverse-based learning may support visuospatial reasoning, self-directed inquiry, goal-directed thinking, and emotionally driven engagement to a greater extent than conventional video-based learning. In other words, the metaverse may provide learners with an integrated learning experience that encompasses cognitive, affective, and motivational processes, which may contribute to their capacity to generate biological knowledge.

Based on these findings, several educational implications can be proposed.

First, educational settings may consider incorporating, where appropriate, immersive, inquiry-based learning designs with high ecological realism, such as those afforded by metaverse environments. Activities that guide students to explore three-dimensional environments, interact with virtual objects, and conduct simulated experiments may help support executive functions and problem-solving skills, while simultaneously visualizing abstract content and linking it to real-world contexts, thereby potentially enhancing learning engagement.

Second, the increased activation observed in prefrontal regions (DLPFC, FP, OFC) in this study may be associated with learners' knowledge generation and the enhancement of affective competencies, providing preliminary neuroscientific evidence that may inform instructional design within similar educational contexts. Specifically, lessons could be designed to cognitively, emotionally, and motivationally engage learners through immersive, inquiry-based activities, thereby supporting meaningful changes in relevant thinking processes. Furthermore, by tracking the brain regions in which significant changes occur, future longitudinal research can further examine the sustained impact of metaverse-based learning on neural plasticity and academic achievement, as well as the generalizability of metaverse applications across different subjects and learning contexts. Such investigations would be necessary to substantiate broader educational applications of metaverse-based learning.

Conflicts of Interest

The author(s) declared no conflicts of interest.

Acknowledgement

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2022S1A5A2A01043191).

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