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Metaverse-Based Self-Regulated Learning in Nursing Dietary Education: Effects on Learning Achievement, Self-Efficacy, Critical Thinking Awareness, and Behavioral Patterns

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Abstract

A central goal of foundational dietary education is to enhance nursing students' learning achievement, self-efficacy, and critical thinking awareness. However, providing personalized guidance in conventional instructional settings remains challenging. To address these limitations, the present study introduces a structured metaverse-based self-regulated learning framework designed to promote personalized, immersive, and contextually rich learning experiences in dietary education. A quasi-experimental study was conducted with 44 undergraduate nursing students enrolled in an introductory course on cancer-preventive dietary practices. Participants were assigned to either a metaverse-based self-regulated learning condition (experimental group) or a conventional 2D video-based instruction condition (control group). Findings indicate that students in the metaverse-based condition demonstrated significantly higher levels of learning achievement, self-efficacy, and critical thinking awareness than peers

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in the conventional instruction group. Exploratory behavioral analyses of the 22 experimental-group participants, categorized by a median split, suggested that learners with higher critical thinking awareness exhibited more structured, reflective, and proactive learning patterns, whereas those with lower awareness relied more on feedback-dependent strategies. Overall, metaverse-based self-regulated learning enhanced learning achievement, self-efficacy, and critical thinking awareness, while providing preliminary insights into learners' behavioral patterns in nursing education.

Keywords
self-regulated learning, interaction dynamics, metaverse environments, critical thinking awareness, learning analytics

Introduction

In nursing and dietary education, learners are expected to develop not only professional knowledge and clinical competencies but also essential 21st-century skills such as critical thinking, problem-solving, collaboration, and adaptability in increasingly complex healthcare environments (Thornhill-Miller et al., 2023). Critical thinking encourages learners to engage with diverse perspectives, thereby fostering inclusivity and more effective collaboration (Barak & Shahab, 2023). It further strengthens learners' ability to evaluate information, solve problems creatively, and make ethically informed decisions. Kurylo et al. (2023) emphasize that critical thinking empowers learners to address misinformation, respond to rapid societal and technological shifts, and act as engaged global citizens capable of contributing positively to society.

Cancer-preventive dietary education is particularly challenging for first-year nursing students because they typically have limited clinical experience and must integrate unfamiliar knowledge of nutrition, cancer risk factors, and preventive care while translating this knowledge into practical dietary decisions (Wilt & Thomson, 2025). The topic requires students not only to recall dietary recommendations but also to evaluate health information, distinguish appropriate from inappropriate dietary choices, and apply preventive principles to realistic situations (Khiri & Howells, 2025). These cognitive and application demands may be difficult for novice nursing students who have not yet developed sufficient clinical reasoning or experience in connecting theoretical knowledge with patient-centered health education (Perez-Garcia et al., 2025). Therefore, instructional approaches that provide contextualized practice, active decision-making, and opportunities for reflection may be especially important for supporting first-year nursing students' learning of cancer-preventive dietary concepts.

However, traditional lecture-based instructional approaches often provide limited opportunities for experiential learning, active engagement, and authentic problem-solving, thereby constraining the development of higher-order thinking skills and learner autonomy required in contemporary healthcare education (Rahimi & Oh, 2024). As a result, technology-enhanced learning approaches have gained increasing attention as innovative strategies for improving student engagement, interactive learning experiences, and competency-based education.

Metaverse-based learning has emerged as a potentially transformative response to the evolving needs of digital-age learners and the global knowledge economy (Hwang & Chien, 2024). The metaverse integrates immersive virtual reality, interactive simulations, and collaborative digital environments, allowing learners to actively participate in realistic and context-rich educational experiences (Aljumaie et al., 2023).

By simulating real-world scenarios and complex problems, metaverse-based learning environments allow learners to engage deeply with content, practice decision-making, and receive real-time feedback, all within a safe, controlled virtual space (Asiksoy, 2023). These features are particularly effective in developing critical competencies required in the 21st century, including digital literacy, cross-cultural communication, and adaptability.

The metaverse environment facilitates personalized learning, which enables differentiated instruction based on individual learner needs, preferences, and performance (Zhao et al., 2022). Such learner-centered environments are theoretically important for fostering self-regulated learning (SRL), as students are required to actively set learning goals, monitor their progress, manage learning strategies, and reflect on their performance within immersive and autonomous virtual settings (Chang & Dao, 2025; Youssef & Alibraheim, 2024; Zimmerman, 1990). Despite the advantages of metaverse-based learning, immersive virtual environments alone do not automatically guarantee effective learning outcomes. Without adequate self-regulation, learners may experience cognitive overload, distraction, reduced learning persistence, or difficulties managing autonomous learning tasks within highly interactive virtual spaces. Therefore, integrating SRL into metaverse-based learning is essential to help learners effectively manage their cognitive, motivational, and behavioral learning processes. The intervention in this study should be understood as a multicomponent instructional framework rather than as an effect of metaverse technology alone. The immersive VR/metaverse environment was expected to provide contextualized presence and experiential engagement; SRL scaffolding was intended to support goal setting, strategic planning, self-monitoring, and reflection; AI chatbot assistance was designed to provide on-demand guidance and individualized support; gamification and scenario branching were intended to sustain engagement while requiring learners to make choices across evolving situations; and immediate feedback and interactive practice were expected to reinforce knowledge application and enable learners to adjust their decisions during learning.

Accordingly, the control condition should not be interpreted as testing metaverse versus 2D learning in isolation. Rather, the study compares a bundled metaverse-based SRL intervention incorporating immersive interaction, SRL scaffolding, AI chatbot assistance, gamified scenario branching, immediate feedback, and interactive practice with a conventional 2D video-based instructional condition. Two-dimensional video-based instruction was selected because it represents a commonly used digital instructional format in higher education and provides a pragmatic comparison for examining the added educational value of the integrated intervention method. Therefore, any between-group differences should be interpreted as the overall effect of the multicomponent metaverse-based SRL learning design relative to the 2D video condition, rather than as evidence of the independent effect of immersion, SRL, AI assistance, gamification, or feedback alone. Nonetheless, there are limited empirical studies combining scenario-based metaverse game technology with self-regulated learning theory (Zimmerman, 1990). To address the need for rigorous empirical investigation into the educational value of this integrated approach and its measurable impacts on learning, the present study adopts a quasi-experimental research design to systematically explore the effects of a metaverse-based self-regulated learning framework on nursing students' learning achievement, self-efficacy, critical thinking awareness, and learning behaviors.

(1) Does metaverse-based self-regulated learning improve students' learning achievement more than two-dimensional (2D) video learning?
(2) Does metaverse-based self-regulated learning improve students' learning self-efficacy more than 2D video learning?
(3) Does metaverse-based self-regulated learning improve students' critical thinking awareness more than 2D video learning?
(4) How do behavioral learning patterns differ between nursing students with high and low levels of critical thinking awareness within a metaverse-based self-regulated learning environment?

Relevant Studies

Metaverse-Based Learning

Metaverse-based learning involves an immersive digital ecosystem embedded in the metaverse, an interconnected, persistent, and interactive virtual realm, where virtual-reality (VR) technologies are leveraged to support education (Wang et al., 2022). It enables learners to engage in real-time, embodied experiences that simulate authentic scenarios, thereby enhancing presence, interaction, and self-regulated learning (Wang, 2024). By combining the sensory immersion of VR with the social and spatial continuity of the metaverse, this educational approach fosters experiential learning, collaboration, and personalized education (Chen et al., 2023). However, immersive learning environments alone may not automatically lead to effective learning outcomes, as students must also actively regulate their cognitive, motivational, and behavioral learning processes to successfully engage in complex virtual learning tasks. Therefore, SRL serves as an important theoretical framework for supporting learners' goal setting, self-monitoring, strategic learning management, and reflective thinking within metaverse-based educational environments (Zimmerman, 1990). In this study, the intervention specifically refers to the integration of SRL strategies into metaverse-based learning activities, rather than the use of the metaverse technology alone.

Across educational contexts, existing studies generally suggest that metaverse-based learning can increase immersion, engagement, self-efficacy, and opportunities for experiential practice, with some studies also reporting improvements in learning achievement, critical thinking awareness, communication, and decision-making (Cho et al., 2024; Jeon et al., 2024; Kim & Kim, 2023; Muthmainnah et al., 2025; Yang & Kang, 2022). Collectively, these findings indicate that immersive and interactive virtual environments may be particularly useful when learning requires contextualized practice and active participation. However, the evidence remains heterogeneous because previous studies have used different platforms, learner populations, instructional activities, and outcome measures, making it difficult to determine whether reported benefits arise from immersion itself or from accompanying instructional features. In addition, many studies emphasize short-term perceptions, engagement, or self-reported outcomes, while evidence concerning sustained cognitive, motivational, and behavioral effects remains less established.

An additional limitation is that metaverse interventions are often implemented as multi-component learning environments rather than as isolated technological treatments. Consequently, the independent contributions of immersive technology, instructional scaffolding, interactive practice, feedback, and other embedded learning supports are not always distinguishable. This uncertainty is particularly important for self-regulated learning (SRL), because immersive environments may provide autonomy and interaction but do not necessarily ensure that learners effectively plan, monitor, regulate, and reflect on their learning. Although prior work has reported positive outcomes from metaverse-based education, relatively few studies have explicitly integrated SRL principles and simultaneously examined learning achievement, self-efficacy, critical thinking awareness, and behavioral learning processes.

These limitations are more pronounced in nursing and dietary education. Existing metaverse research has been conducted across clinical simulation, career mentoring, handoff education, and language learning, but empirical evidence remains limited regarding cancer-preventive dietary education, where novice nursing students must connect preventive knowledge with contextualized dietary judgments and decision-making. Furthermore, conventional 2D video-based learning remains widely used in higher education (Ashour et al., 2023; Navarrete et al., 2025), yet limited evidence has examined whether an SRL-supported metaverse learning environment provides additional benefits over such conventional digital instruction. Therefore, further research is needed to evaluate the educational outcomes of an integrated metaverse- based SRL approach and to explore how learners behave within this environment.

Within nursing and health education, immersive learning is especially relevant because it can provide contextualized practice for clinical and health-related decision-making in safe simulated environments. Nursing-oriented metaverse applications, including clinical simulation and handoff education, have shown potential benefits for self-efficacy, critical thinking, communication, and engagement (Cho et al., 2024; Yang & Kang, 2022). However, immersion alone does not explain how students manage complex learning tasks. SRL is therefore particularly important because learners must set goals, monitor understanding, adapt strategies, and reflect on decisions while developing professional judgment. Integrating SRL scaffolding with immersive learning may provide a stronger pedagogical basis than technology-centered immersion alone, although empirical evidence examining this integration in nursing and preventive-health education remains limited.

Learning Behavior

Learning behavior refers to the observable actions, strategies, and cognitive and affective responses that learners exhibit during the process of acquiring knowledge, skills, attitudes, or values (Chou et al., 2023; Liu, Shadiev, & Cao, 2025). Such behaviors include instructional engagement, task completion, problem-solving approaches, peer or material interaction, help-seeking, self-regulation, and emotional responses to learning tasks (Li et al., 2021). In educational research, learning behaviors are often categorized based on cognitive engagement (e.g., elaboration and reflection), metacognitive strategies (e.g., planning, monitoring, and evaluation), and social or collaborative interactions (Liu, Shadiev, & Cao, 2025; Wang et al., 2023). Hsiao et al. (2023) reported that learning behavior patterns are critical indicators of students' learning processes and outcomes and can be quantitatively or qualitatively analyzed through methods such as coding schemes, behavioral trace data, or learning analytics.

A variety of advanced technologies have been developed in previous studies to systematically collect, analyze, and interpret learners' behavioral data during educational activities (Li et al., 2021; Liu, Shadiev, & Cao, 2025; Wang et al., 2023). Investigators have used educational data-mining and learning-analytics tools to analyze interaction sequences and identify engagement patterns, knowledge gaps, and learners at risk of poor learning outcomes (Nouira et al., 2019; Romero & Ventura, 2020). Researchers have also made use of critical log data in learning-management systems such as Moodle (Rebelo Marcolino et al., 2025), Canvas (Ngulube & Ncube, 2025), and Blackboard (Goh, 2026), including time-on-task, page visits, assignment submissions, and forum interactions (Pansri et al., 2024). These platforms thus offer foundational behavioral insights through passive tracking.

More immersive behavioral data are collected through learning log tracking technology, which records learners' gaze paths, fixation points, and attention distribution, and is particularly useful in screen-based learning environments or simulated settings (Klein-Latucha & Hershkovitz, 2024; Zeng, 2024). In serious game VR learning environments, log data can capture real-time decision-making processes, task completion trajectories, and feedback interactions (von Kotzebue et al., 2022). Within educational contexts, these data inform classroom activity design and yield behavioral metrics, such as score variability among high achievers and inquiry-based actions, that may indicate emotional engagement or cognitive load (Li et al., 2021; Liu, Shadiev, & Cao, 2025; Wang et al., 2023). Further, advances in computer vision have made it possible to use recognition recorders to capture learning engagement in online game-based environments. For example, Li et al. (2021) designed a concept mapping-based two-tier testing strategy within a digital learning context to analyze students' behavioral patterns, demonstrating improvements in learning performance. Chou et al.

(2023) proposed a cognitive-based game mechanism for mobile education aimed at promoting students' cognitive engagement and flow states based on the analysis of metaverse-based learning behavioral patterns.

In nursing and health education, learning analytics can complement conventional outcome measures by revealing how learners engage with simulated tasks, seek feedback, revise decisions, and regulate their learning processes. Behavioral trace data from immersive or serious-game environments can capture decision sequences, task-completion trajectories, and feedback interactions that are difficult to observe through post-test scores alone (von Kotzebue et al., 2022). Such process-oriented evidence is particularly relevant to SRL because it can provide observable indicators of planning, monitoring, help-seeking, strategy adjustment, and reflection. Nevertheless, the application of learning analytics to immersive nursing and preventive-health education remains comparatively underdeveloped. Empirical studies examining behavioral processes in cancer-preventive dietary education are scarce, and evidence based on small or single-group behavioral samples should be interpreted as exploratory. To address this gap, the present study explores behavioral patterns among students with different levels of critical thinking awareness within the metaverse-based SRL environment.

Lag sequential analysis (LSA) is particularly suitable for RQ4 because the question focuses on how learners' behaviors unfold as sequential patterns within the metaverse-based SRL environment. Conventional indicators such as behavioral frequencies show how often an action occurs, whereas time-on-task indicates the duration of engagement; neither identifies whether particular behaviors systematically precede or follow others. In contrast, LSA tests transitions between successive coded behaviors and identifies sequences that occur more often than expected by chance. This makes it possible to examine process-level patterns of self-regulation, such as whether feedback is followed by strategy adjustment, or whether reflection leads to renewed task engagement. For RQ4, LSA therefore provides exploratory evidence about how students with higher versus lower critical thinking awareness differ in the organization and progression of their learning behaviors, contributing insights beyond simple frequency counts or accumulated learning time.

Metaverse-Based Self-Regulated Learning Approach

The proposed metaverse-based self-regulated learning approach was developed using Unity software. Unity was chosen for its accessibility, rich interactivity, and synchronous multi-user support, features particularly well suited for immersive instructional design. Within this platform, nursing students engaged in inquiry-driven and exploratory learning activities guided by structured learning worksheets situated in foundational dietary scenarios related to cancer prevention. The integration of gamified elements with self-regulated learning strategies and generative-AI capabilities allowed for the delivery of personalized, interactive instruction.

The Unity environment further enabled the simulation of complex decision-making processes related to cancer preventive nutrition. The structure comprised two core components (see Figure 1): an instructional content editor and an interactive learner

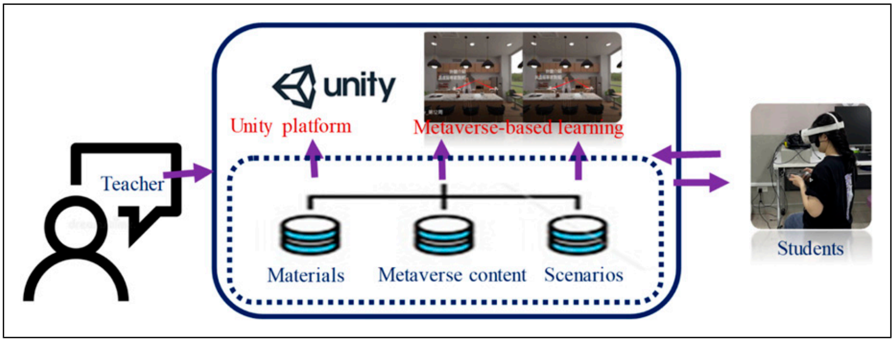

Figure 1. Metaverse-based learning platform structure

module. These included embedded functionalities such as task sequences, hint systems, and virtual treasure chests. The platform also enabled the customization of educational activities, implementation of scoring rubrics, and real-time data monitoring through backend database integration. Moreover, it supported AI-based dialogue systems and the design of non-player characters, thereby enabling seamless integration with external AI engines such as ChatGPT to generate dynamic, automated interactions with virtual agents.

This study is grounded in Zimmerman's (1990) self-regulated learning theory, which outlines three phases (forethought, performance, and self-reflection) that emphasize the dynamic interactions between personal, behavioral, and environmental factors. The social-cognitive framework views learning as a cycle in which individuals regulate thoughts, actions, and motivations to reach academic goals (Kesuma et al., 2020). Within this model, learners develop self-regulatory capabilities through processes such as self-observation, self-judgment, and strategy adjustment, all of which contribute to building academic self-efficacy.

Course Design

In classroom contexts shaped by curricular structures, self-regulated learning researchers have increasingly examined how students initiate, manage, and sustain their learning efforts. The triadic formulation provides a valuable lens for understanding and enhancing nursing students' learning achievement and their capacity for independent learning. By incorporating the self-regulated learning framework, the approach employed in this study is intended to enhance nursing students' capacity for autonomous learning and foster improved educational outcomes within the context of scenario-based nutrition instruction.

In the virtual environment employed in this study, nursing students assumed the role of healthcare providers to simulate real-world decision-making in a metaverse kitchen designed for health education. They engaged in role-playing tasks such as selecting phytochemical-rich foods, reading virtual nutrition labels, and preparing meals aligned with cancer prevention guidelines. Learners received instant feedback from an AI nutrition coach and joined group discussions in a simulated dining area. This immersive setting was designed to foster experiential learning, promote critical thinking awareness, and improve nursing students' ability to apply dietary knowledge to real-world practice. The structured application of behavioral coding schemes allowed for examination of nursing students' cancer-prevention dietary self-efficacy and critical thinking awareness. This metaverse-based approach was implemented to integrate self-regulated learning strategies into cancer prevention dietary education.

The metaverse-based self-regulated learning model encompasses reciprocal influences among the person (self), behavior, and the environment. In the person phase (Figure 2), nursing students initiate their engagement by setting personal learning goals and managing their cognitive resources within a metaverse-based environment. At this stage, learners regulate their motivation and goal-setting processes through reflective thinking supported by prompts and digital mentors in AI-generated virtual scenarios while completing structured dietary tasks. Students use AI chatbots, scenario simulations, and video summaries to actively explore classification activities related to cancer prevention and food, exhibiting behavioral self-regulation. Simultaneously, environmental self-regulation occurs as learners navigate the immersive learning spaces, where participation levels, interaction intensity, and learning sequences are recorded. Students are encouraged to interpret visualized dietary data, engage in prompt-based inquiries, and discuss ethical risks using guided learning worksheets. These interactions foster strategic learning behavior and elicit enactive feedback, thereby strengthening self-motivation and preparing learners to achieve higher cognitive and critical thinking goals.

In the behavior phase (Figure 3), the observable actions and learning strategies that nursing students employ while interacting with tasks are emphasized. Behavioral self-

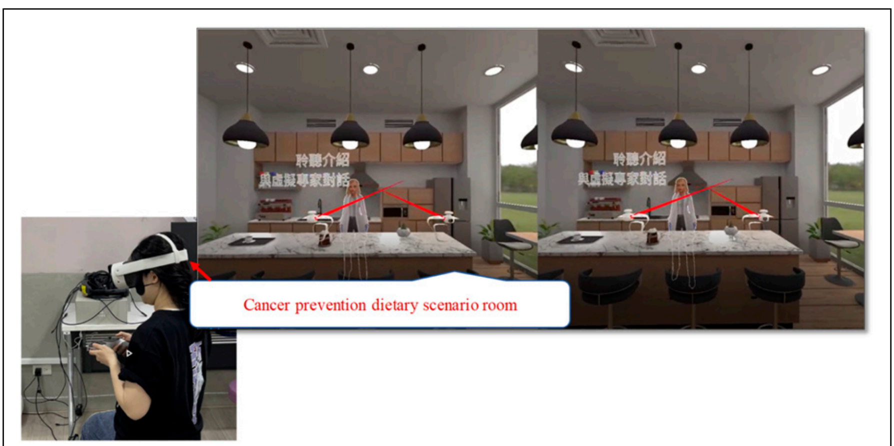

Figure 2. Example virtual scene depicting the person (self) phase

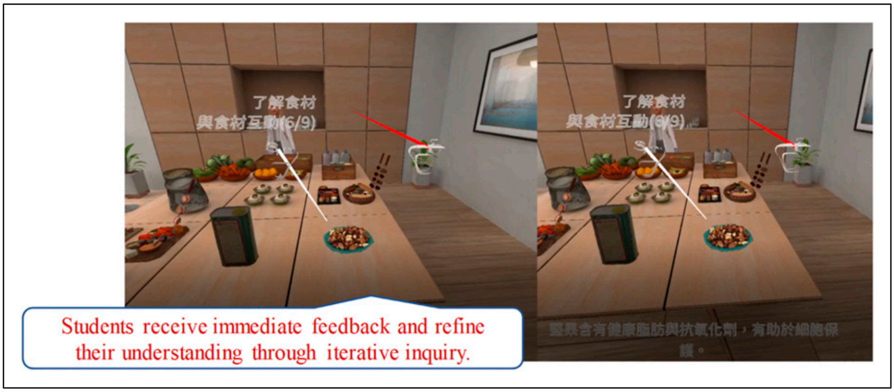

Figure 3. Example virtual scene depicting the behavior phase

regulation is reflected through students' active participation, task execution, and real-time decision-making in response to dynamic scenarios. Learners' interactions are captured via video recordings that document ten-minute exploratory activities during the dietary cancer prevention learning process. These videos include observable indicators such as task completion, verbal reasoning, accuracy of dietary classifications, and reflective statements. Such behavior represents the enactment of self-regulation strategies in response to both internal goals (person) and external conditions (environment). During this self-management phase, students are required to establish appropriate dietary classification criteria aligned with cancer-prevention principles. Students engage in simulated clinical dialogue and decision-making while navigating the virtual environments in Unity, where they receive immediate feedback and refine their understanding through iterative inquiry. This behavior is further deepened through metacognitive reflection as students reassess and adjust their strategies after experiencing success or failure in simulated cases. By integrating structured prompts and interactive, clickable dialogue choices, students are encouraged to apply theoretical frameworks and engage in critical thinking processes. These interactive behaviors not only support the development of accurate dietary judgment but also foster emotional engagement and deeper understanding of person-centered care in cancer prevention contexts. This approach strengthens students' behavioral self-regulation through the alignment of their observed learning actions with their internal motivation (person) and environmental supports (environment), which enhances critical thinking awareness and clinical reasoning during dietary assessment.

The environment phase (Figure 4) emphasizes how external learning conditions and supports shape nursing student behavior and contribute to personal self-regulation. Learners interact with a carefully designed metaverse environment that personalizes and contextualizes cancer prevention dietary education, thereby promoting sustained engagement by embedding gamified learning elements, scenario branching, and AI-supported decision pathways. Within this immersive virtual environment, students are not passive recipients of information, but active agents navigating complex tasks. For

Figure 4. Example virtual scene depicting the environment phase

example, when prompted with questions such as “What elements should be included in a phytochemical-rich meal?”, students’ responses influence the progression of the learning scenario. Based on their dietary decisions, they are redirected into different simulated care pathways that mirror real-world variations. The platform thus enables the strategic use of environmental resources, such as interactive feedback loops, visual data representations, and AI-generated coaching that guide students to revise misjudgments and reflect on their reasoning processes. Learners can adjust their dietary classification strategies with the assistance of generative AI, which helps them gain clarity on the clinical importance of accurate judgments for cancer prevention, especially in time-sensitive cases. This mechanism highlights the interplay between environment and behavior, where adaptive changes in the virtual setting provoke deeper cognitive engagement and emotional investment. Whereas conventional instruction relies heavily on passive learning and fixed procedural steps, this metaverse-based method allows for authentic decision-making in high-context scenarios. By visualizing the consequences of their actions, students develop both knowledge and critical thinking awareness that allow them to recognize how timely dietary decisions can impact the health trajectory of a patient. In this way, the learning environment serves not only as a backdrop, but as an active regulatory agent that dynamically influences learners’ behavior and supports their self-regulated learning journey in cancer prevention dietary education.

Figure 5 presents examples of the VR course on cancer-preventive dietary practices, which was designed to provide an immersive and interactive learning environment that supports experiential learning and healthy decision-making. Students interact with virtual food items using VR controllers to explore nutritional information, complete meal-planning tasks, and receive immediate feedback. The figure illustrates different learning perspectives and demonstrates how students actively engage with the VR environment through real-time interaction and task-based activities.

Figure 5. Example of the VR course

Method

A quasi-experimental quantitative study supplemented by exploratory behavioral learning analytics was adopted to evaluate the implementation of a self-regulated learning instructional approach within a metaverse-based environment aimed at enabling nursing students to actively engage in inquiry and knowledge construction through guided learning worksheets embedded in foundational dietary scenarios for cancer prevention.

Research Design

A quasi-experimental design was employed to compare two instructional methods: an integrated metaverse- based SRL method and conventional 2D video-based blended instruction, with respect to nursing students' learning performance. Participants were enrolled in a foundational course on dietary practices for cancer prevention. Data collection was conducted using previously validated and reliability-tested instruments designed to measure learning achievement, self-efficacy, critical thinking awareness, and learning behavior.

All instructional sessions were facilitated by the same educator, who possessed over five years of professional teaching experience. A blended learning approach was implemented by combining face-to-face classroom instruction with digital learning activities delivered through virtual learning platforms. Both groups received the same instructional content, learning objectives, course duration, and assessment tasks to ensure instructional consistency. This format allowed learners to access course content using Oculus Quest 3. The experimental group participated in a metaverse-based learning environment integrated with SRL scaffolding strategies and AI chatbot assistance designed to support goal setting, self-monitoring, reflective learning, and interactive problem-solving. In contrast, the control group received conventional blended instruction through 2D video-based learning materials and teacher-guided classroom activities without metaverse immersion or SRL-based supports. Instructional time, learning objectives, and assessment conditions were held constant across both groups to control for potential confounding variables. However, the two conditions differed simultaneously across several intervention components, including technology modality, level of immersion and interactivity, AI chatbot support, gamification/scenario-based activities, immediate feedback, and SRL scaffolding. Therefore, the present design supports a comparison of the two instructional methods as a whole, rather than causal claims regarding the isolated effects of metaverse technology, SRL scaffolding, AI support, gamification, feedback, or interactivity.

Participants and Setting

A total of 52 first-year undergraduate nursing students enrolled in an introductory nutrition course were initially recruited for this study. None of the participants had prior exposure to VR platforms. Among them, two students withdrew from the course, and six did not complete either the pretest or related questionnaires, resulting in a final sample of 44 students, reflecting an attrition rate of 15%. These students were divided into two groups: the experimental group (n = 22) received metaverse-based self-regulated learning instruction, while the control group (n = 22) received conventional video-based instruction without VR integration. Group assignment was conducted using a non-random allocation procedure consistent with quasi-experimental design constraints. Table 1 shows the demographic and background characteristics of the final sample were as follows: the participants had a mean age of 18.86 years (SD = 0.67;

Table 1. Demographic Characteristics

Characteristic	Overall (N = 44)	Experimental (n = 22)	Control (n = 22)	Baseline p-value
Age, years, M (SD)	18.86 (0.67)	18.82 (0.66)	18.91 (0.68)	.66
Age range, years	18–21	18–20	18–21	—
Female, n (%)	39 (88.6%)	20 (90.9%)	19 (86.4%)	.64
Male, n (%)	5 (11.4%)	2 (9.1%)	3 (13.6%)	
Prior nutrition-related academic learning, n (%)	12 (27.3%)	6 (27.3%)	6 (27.3%)	1.00
Prior clinical/healthcare experience, n (%)	4 (9.1%)	2 (9.1%)	2 (9.1%)	1.00

range = 18–21), with 39 (88.6%) female students and 5 (11.4%) male students. Regarding relevant academic and clinical experience, 12 (27.3%) participants had prior nutrition-related academic learning experience, and 4 (9.1%) had prior clinical or healthcare-related experience. These characteristics were also examined by group, and no significant baseline differences were observed between the experimental and control conditions (all $p > .05$), indicating comparable demographic and background characteristics. Participant flow by condition was documented separately as follows. In the experimental condition, 26 students were initially enrolled; 2 withdrew from the course and 2 had incomplete pretest or questionnaire data, leaving 22 participants included in the final analysis. In the control condition, 26 students were initially enrolled; 1 withdrew and 3 had incomplete assessments, leaving 22 participants included in the final analysis. Thus, the final analytic sample comprised 44 participants (experimental, $n = 22$; control, $n = 22$).

To evaluate whether the sample size was adequate, a post hoc power analysis was conducted using G*Power version 3.1 (Faul et al., 2007, 2009). The analysis was based on an ANCOVA design with two groups, an alpha level of .05, a medium effect size ($f = 0.25$), and a total sample size of 44 participants (22 per group). The computed statistical power was 0.81, which exceeds the recommended threshold of 0.80, suggesting that the sample size was adequate to detect statistically meaningful effects. Both groups studied identical curricular content related to the foundational nutrition course. No student had previously been instructed via metaverse-based self-regulated learning. All instruction was facilitated by the same educator, who had five years of experience in teaching with VR technologies. The experimental condition was delivered over 2 weeks, with approximately 60 min of instruction per week, for a total instructional duration of approximately 2 h. The control condition was delivered over the same 2-week period, with approximately 60 min of instruction per week, for a total instructional duration of approximately 2 h. Thus, the total instructional time was equivalent across conditions.

Study Variables

The independent variable in this study was the metaverse-based self-regulated learning approach implemented in a foundational course on dietary practices for cancer prevention among nursing students. The dependent variables included students' learning achievement, self-efficacy, critical thinking awareness, and learning behavior. These variables were assessed using previously validated and reliability-tested instruments.

Experimental Procedure

The study was conducted over a five-week period (Figure 6). In the initial week, the instructor introduced the course goals and explained the assigned foundational nutrition learning tasks. Students also completed a pre-intervention survey designed to assess their baseline learning achievement, self-efficacy, and critical thinking awareness. During weeks three and four, the experimental group participated in the

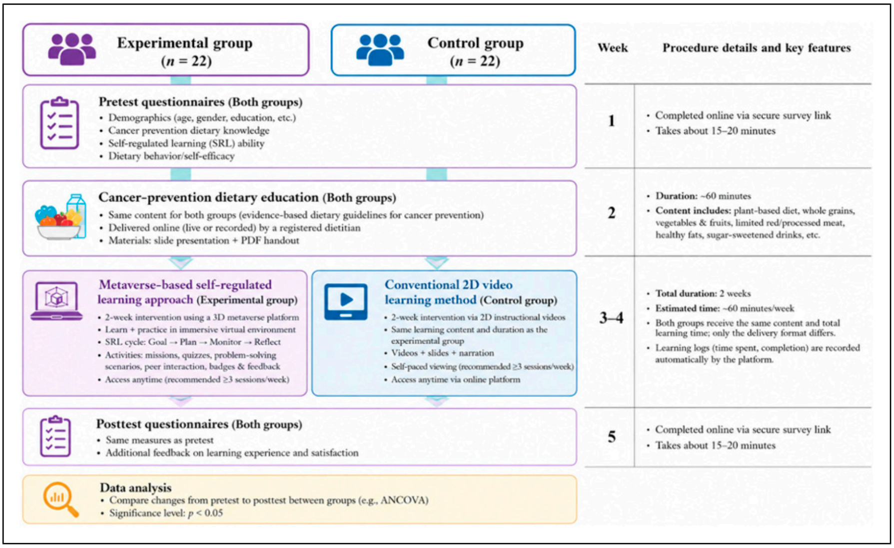

Figure 6. Experimental procedure

metaverse-based self-regulated learning approach, which involved completing scenario-based nutrition tasks with the aid of learning worksheets. Meanwhile, the control group received equivalent video-based instruction accompanied by structured worksheets. The instructional content, activity duration, and instructor were identical to those of the experimental group. The only difference between the two groups was the learning environment (metaverse-based self-regulated learning vs. 2D video-based instruction).

At the conclusion of the intervention period, participants in both groups were asked to complete a post-intervention questionnaire to re-evaluate their progress across the three target competencies. Additionally, those in the experimental group were required to upload video recordings of their metaverse-based learning sessions to the online learning platform for documentation and analysis. These recordings were subsequently coded using predefined behavioral analysis criteria to ensure consistency and analytical reliability.

Measuring Tools

Two experienced educators, each with over five years of expertise in the subject area, collaboratively created both pretest and posttest questionnaires. The pretest served to evaluate nursing students' prior understanding of the prior knowledge of cancer-preventive nutrition, establishing a baseline for learning achievement. The posttest was utilized to measure nursing students' progress and concept after the instructional period. Each assessment consisted of 10 questions, with the highest attainable score being 100. Example items from the pretest and posttest assessments are provided in the

Appendix. The internal consistency of the assessments was evaluated using the Kuder-Richardson Formula 20 (KR-20). Results indicated a reliability coefficient of 0.75 for the pretest and 0.76 for the posttest, demonstrating acceptable internal consistency for research purposes. The pretest and posttest were designed as parallel 10-item forms aligned with the same cancer-preventive dietary learning objectives and content domains. A test blueprint ensured comparable content coverage. Three experts in nursing and health education reviewed both forms, yielding I-CVI values ranging from 0.83 to 1.00 and an S-CVI/Ave of 0.93. Pilot item analysis showed comparable mean item-difficulty indices for the pretest (0.62) and posttest (0.60), supporting the equivalence of the two forms and the interpretation of score changes as learning gains rather than differences between test forms.

This study employed a modified version of the self-efficacy scale originally created by Pintrich et al. (1991) and later adapted by Chang et al. (2024). The questionnaire consisted of eight items, including "I believe I will receive an excellent grade in this activity" and "I expect to do well in this activity." Participants responded using a 5-point Likert scale, where higher ratings indicated higher self-efficacy. The reliability of the instrument was supported by a Cronbach's alpha of 0.84, indicating good internal consistency.

To measure nursing students' critical thinking awareness, the study adopted an adapted version of the critical thinking awareness scale, initially created by Lin et al. (2019). In this study, critical thinking awareness was operationalized as learners' self-reported awareness of engaging in critical reflection and evaluation during learning, rather than as an objective measure of critical thinking ability, disposition, or observable performance. The scale includes six statements rated on a 5-point Likert scale. Higher scores indicate a greater level of critical thinking awareness. The instrument demonstrated strong internal reliability, with a Cronbach's alpha coefficient of 0.89.

To measure nursing students' *learning behaviors*, the study adopted a modified behavioral coding scheme to investigate learning behaviors associated with self-reported critical thinking awareness in the VR environment. These coded behaviors were analyzed as behavioral correlates of critical thinking awareness and were not treated as direct measures of critical thinking ability or performance. The scheme was based on the framework proposed by Li et al. (2021) and included twelve categories of interaction (Table 2). The critical thinking awareness scale consisted of six items rated on a 5-point Likert scale, with total scores ranging from 6 to 30. For the exploratory behavioral analysis, participants were classified based on their posttest scores using the verified median of 27 as the cut-off. Students scoring above the median were classified as the higher-awareness group (n = 12), whereas those scoring at or below the median were classified as the lower-awareness group (n = 10).

Each interaction code corresponded to a specific type of learning behavior. Two independent raters, one with expertise in digital learning, and the other with a background in metaverse-based instructional methods, manually coded the screen-recorded VR sessions. Inter-rater reliability was high, with a Cohen's kappa coefficient of 0.88, reflecting strong agreement between coders (Lavrakas, 2008). Discrepancies were resolved through consensus discussions to ensure consistency and accuracy in the

Table 2. Behavioral Patterns Coding Scheme

Code	Description	Behavior explanation
R	Reading learning content	Open VR instructional materials or interact with virtual characters to receive content.
P	Planning learning tasks	Set learning goals or select VR modules based on personal learning plans.
Q	Answering the VR quiz correctly	Correctly answer a question and earn virtual points.
W	Wrong answer	Incorrect answer: learner is guided to review relevant VR learning content.
S	Self-monitoring progress	Check progress in the VR environment.
M	Managing learning strategies	Choose or switch learning strategies (e.g., repeating scenarios, requesting hints).
E	Exploring VR learning environments	Interact with different scenarios, characters, or objects in the VR world.
C	Consulting VR guides	Open and review VR-integrated guidance tools.
V	VR task success	Complete learning challenge or scenario with full marks.
L	Logging out or session completion	Exit the VR session after completing assigned learning activities.
A	Avoiding tasks (e.g., skipping or quitting mid-task)	Player exits or skips the task before completion.
T	Time management	Student sets timers or checks remaining time for VR tasks.

final coding results. A predefined coding protocol was followed to standardize the coding process and minimize subjective bias.

Data Analysis

Quantitative analyses were conducted using ANCOVA with SPSS version 22.0 (IBM, Armonk, NY, USA). Learners' behavioral patterns within the metaverse-based self-regulated learning environment were captured and examined through lag sequential analysis using GSEQ software (Bakeman & Quera, 1995). This analytical approach detects temporal relationships among coded behaviors, which allows researchers to explore behavioral transitions embedded in dynamic interaction sequences. Prior to conducting ANCOVA, all relevant statistical assumptions, including normality, homogeneity of variances, and homogeneity of regression slopes, were systematically assessed. The results are presented as weighted behavior networks, offering graphical representations of behavior co-occurrence patterns for each defined analytical unit in the dataset. Effect sizes were calculated to determine the magnitude of observed differences, thereby complementing statistical significance testing.

Results

Significant improvements in nursing students' learning achievement, self-efficacy, critical thinking awareness, and learning behaviors were observed in the experimental group receiving metaverse-based self-regulated learning instruction. The metaverse-based approach was especially beneficial in encouraging learners to actively participate in complex decision-making tasks related to nutrition, thereby demonstrating higher-order thinking processes within the immersive learning context.

Learning Achievement

An independent samples t-test was conducted to examine baseline equivalence between the two groups, and the results indicated no statistically significant difference in pre-test learning achievement scores, t (42) = 0.91, p = .367, confirming the comparability of the groups prior to the intervention.

The descriptive statistics for the pre-test and post-test scores of learning achievement are presented in Table 3. At the pre-test stage, the experimental group (M = 55.46, SD = 7.39) and the control group (M = 52.73, SD = 11.93) demonstrated comparable baseline performance. After the intervention, the experimental group showed a substantial increase in learning achievement (M = 80.00, SD = 5.56), whereas the control group achieved a lower post-test mean score (M = 63.18, SD = 13.05). Therefore, ANCOVA was performed using the pre-test scores as the covariate and post-test scores as the dependent variable.

The results of the Shapiro-Wilk test indicated that the data did not significantly deviate from normality (W = 0.90, $p > .05$). Levene's test confirmed the assumption of homogeneity of variances (F [1, 42] = 3.41, p = .07), In addition, the test for homogeneity of regression slopes was not significant, F (1,41) = 0.82, p = .37, indicating that the assumption of ANCOVA was met. Therefore, ANCOVA was employed to analyze the differences in learning outcomes between the two groups (Table 4).

The results demonstrate that nursing students who engaged in the metaverse-based self-regulated learning approach (M = 79.85, SE = 2.16) significantly outperformed those who followed the conventional video-based learning approach (M = 63.33, SE = 2.16; F [1, 41] = 28.88, $p < .001$). The adjusted mean difference between the experimental and control groups was 16.52 (95% *CI* [10.31, 22.73]).

The metaverse-based self-regulated learning approach thus contributed to a marked improvement in nursing students' learning achievement. The calculated effect size (partial $\eta^2 = 0.413$) exceeded the threshold of 0.138, indicating a strong and meaningful

Table 3. Descriptive Statistics for Learning Achievement

Group	N	Pre-test mean	Pre-test SD	Post-test mean	Post-test SD
Experimental group	22	55.46	7.39	80.00	5.56
Control group	22	52.73	11.93	63.18	13.05

Table 4. ANCOVA Results for Learning Achievement

Group	*N*	Mean	*SD*	Adjusted mean	Std. error	*F*	Partial η^2
Experimental group	22	80.00	5.56	79.85	2.16	28.88***	0.413
Control group	22	63.18	13.05	63.33	2.16		

***p < .001.

impact. Overall, these findings confirm that nursing students instructed using the metaverse-based self-regulated learning approach achieved significantly higher posttest scores than those receiving conventional instruction.

Learning Self-Efficacy

An independent samples t-test further confirmed that there was no statistically significant difference between the two groups at the pretest stage, $t\,(42) = -0.80$, $p = .43$, indicating acceptable baseline equivalence in learning self-efficacy. Table 5 shows that the baseline descriptive statistics demonstrated that participants in the experimental group (M = 3.50, SD = 0.59) and the control group (M = 3.65, SD = 0.65) exhibited comparable levels of learning self-efficacy prior to the intervention. Following the intervention, the experimental group demonstrated a higher post-test mean score (M = 4.76, SD = 0.41), whereas the control group obtained a lower post-test score (M = 4.24, SD = 0.45). To further examine whether the observed differences were statistically significant while controlling for pre-test scores, an ANCOVA was conducted.

The Shapiro-Wilk test yielded a statistic of 0.88 with a p-value greater than 0.05, suggesting that the dataset did not significantly deviate from normality. In addition, Levene's test confirmed the equality of variances (F [1, 42] = 0.03, p = .863). The assumption of homogeneous regression slopes was also satisfied (F [1, 40] = 0.75, p = .392). These values were verified directly from the statistical output to ensure accurate reporting and interpretation. Given that all assumptions were met, ANCOVA was conducted using pretest learning self-efficacy scores as the covariate and posttest scores as the dependent variable (Table 6).

Results indicate that learners who engaged in metaverse-based self-regulated learning (M = 4.74, SE = 0.10) showed significantly higher levels of learning self-efficacy compared to the control group (M = 4.26, SE = 0.10; F [1, 41] = 9.16, p < .01). The adjusted mean difference between the experimental and control groups was 0.48 (95% *CI* [0.16, 0.80]). These results demonstrate that the metaverse-based self-

Table 5. Descriptive Statistics for Learning Self-Efficacy

Group	N	Pre-test mean	Pre-test SD	Post-test mean	Post-test SD
Experimental group	22	3.50	0.59	4.76	0.41
Control group	22	3.65	0.65	4.24	0.45

Table 6. ANCOVA Results for Learning Self-Efficacy

Group	*N*	Mean	*SD*	Adjusted mean	Std. error	*F*	Partial η^2
Experimental group	22	4.76	0.41	4.74	0.10	9.16**	0.183
Control group	22	4.24	0.45	4.26	0.10		

$^{**}p < .01$.

regulated learning approach provided a significant advantage in fostering nursing students' confidence in their learning abilities. The calculated effect size (partial η^2 = 0.183) exceeded the conventional threshold of 0.138, indicating a substantial and practically meaningful impact. The implementation of the metaverse-based self-regulated learning approach was thus effective in significantly enhancing nursing students' learning self-efficacy compared to conventional instructional approaches.

Critical Thinking Awareness

An independent samples t-test indicated no statistically significant difference between the two groups at the pretest stage, t (42) = 0.86, p = .39, supporting baseline equivalence in critical thinking awareness prior to the intervention.

The descriptive statistics for critical thinking awareness are presented in Table 7. At the pre-test stage, the experimental group (M = 4.51, SD = 0.48) and the control group (M = 4.37, SD = 0.59) demonstrated relatively similar baseline levels of critical thinking awareness. After the intervention, the experimental group obtained a higher post-test mean score (M = 4.59, SD = 0.39) compared with the control group (M = 4.19, SD = 0.46). Descriptively, the experimental group showed only a small increase from pretest to posttest (M = 4.51 to 4.59), while its posttest mean remained higher than that of the control group.

These descriptive results indicate a greater improvement in critical thinking awareness among nursing students who participated in the metaverse-based self-regulated learning approach. To further determine whether the observed differences were statistically significant while controlling for pre-test scores, an ANCOVA was conducted.

The Shapiro-Wilk test returned a value of 0.90 with a p-value above 0.05, indicating that the data did not significantly violate the assumption of normality. Levene's test further confirmed that the variances were equal across the groups (F [1, 42] = 1.84, p = .182). In addition, the assumption of homogeneity of regression slopes was supported,

Table 7. Descriptive Statistics for Critical Thinking Awareness

Group	*N*	Pre-test mean	Pre-test SD	Post-test mean	Post-test SD
Experimental group	22	4.51	0.48	4.59	0.39
Control group	22	4.37	0.59	4.19	0.46

as there was no significant interaction effect between the covariate and the independent variable (F [1, 40] = 3.97, p = .053). These assumption test values were verified directly from the original statistical output to ensure accurate transcription and interpretation. Based on these assumptions being satisfied, ANCOVA was performed to assess differences in posttest critical thinking awareness between groups while controlling for pretest performance (Table 8).

The findings show that nursing students in the experimental group who experienced metaverse-based self-regulated learning demonstrated significantly higher critical thinking awareness (M = 4.58, SE = 0.09) than those in the conventional video-based instruction group (M = 4.20, SE = 0.09; F [1, 41] = 8.74, p < .01. After controlling for pretest scores, the adjusted mean difference between the experimental and control groups was 0.38 (95% *CI* [0.12, 0.64]).The observed effect size (partial η^2 = 0.176) exceeded the standard benchmark of 0.138, indicating a substantial and practically meaningful effect. These outcomes collectively indicate that incorporating metaverse-based self-regulated learning meaningfully improved nursing students' critical thinking awareness compared to conventional instructional approaches. After adjustment for pretest scores, the experimental group had significantly higher posttest critical thinking awareness than the control group; this finding should be interpreted as an adjusted between-group difference rather than as evidence of a large within-group improvement.

Analysis of Learning Behavior Patterns

According to Chang et al. (2025), to analyze behavioral trends within the metaverse-based self-regulated learning framework, participants in the experimental group were divided into high and low critical thinking awareness cohorts based on their pre-intervention questionnaire scores. A score of 15 was used as the median split nursing students scoring above this threshold were classified as high-level critical thinkers, while those with scores of 15 or below were placed in the low-level group.

The results of the lag sequential analysis for nursing students with higher critical thinking awareness are presented in Table 9, and highlight 20 statistically significant behavioral patterns. Meanwhile, Table 10 summarizes the behavior sequences observed among nursing students with lower critical thinking awareness, which identify 16 significant sequences determined by z-scores greater than 1.96 (Bakeman & Gottman, 1997). For instance, the transition from R → P indicates that nursing students often plan learning tasks (P) after reading content (R), which reflects goal-setting

Table 8. ANCOVA Results for Critical Thinking Awareness

Group	*N*	Mean	*SD*	Adjusted mean	Std. error	*F*	*Partial* η^2
Experimental group	22	4.59	0.39	4.58	0.09	8.74**	0.176
Control group	22	4.19	0.46	4.20	0.09		

**p < .01.

Table 9. High Critical Thinking Awareness Subgroup Adjusted Residuals

Given:	R	P	Q	W	S	M	E	C	V	L	A	T
R	0	12.44[a]	−2.17	−1.37	−1.31	−1.31	−1.63	−1.37	−1.57	−1.8	−1.37	−1.3
P	−1.34	0	3.64[a]	−1.43	2.22[a]	−1.36	−1.69	−1.43	−1.63	−1.88	5.43[a]	−1.36
Q	−1.46	−2.25	0	8.06[a]	−0.64	−1.48	−1.85	−1.56	6.82[a]	−2.05	−1.56	−1.48
W	1.54	−1.43	−1.56	0	−0.94	−0.94	−1.17	4.84[a]	−1.13	3.36[a]	−0.99	−0.94
S	−0.88	-1.36	−1.48	−0.94	0	13.09[a]	−1.11	−0.94	−1.07	−1.23	−0.94	−0.89
M	−0.88	−1.36	−1.48	−0.94	−0.89	0	6.26[a]	−0.94	−1.07	−1.23	3.93[a]	−0.89
E	−1.09	−1.69	4.4[a]	−1.17	−1.11	−1.11	0	3.87[a]	0.47	−1.54	−1.17	−1.11
C	−0.92	−1.43	3.25[a]	−0.99	−0.94	−0.94	3.87[a]	0	−0.08	−1.3	−0.99	−0.94
V	−1.05	−1.63	−1.78	−1.13	−1.07	−1.07	−1.33	−1.13	0	11.02[a]	−1.13	−1.07
L	10.2[a]	-1.26	−1.37	−0.87	−0.83	−0.83	−1.03	−0.87	−0.99	0	−0.87	0.54
A	−0.92	−1.43	−1.56	−0.99	−0.94	−0.94	−1.17	1.34	−1.13	−1.3	0	11.27[a]
T	−0.83	−1.29	−1.41	-0.89	7.13[a]	−0.85	3.35[a]	−0.89	−1.02	−1.17	−0.89	0

[a]Z-score > 1.96.

Table 10. Low Critical Thinking Awareness Subgroup Adjusted Residuals

Given:	R	P	Q	W	S	M	E	C	V	L	A	T
R	−1.56	12.92[a]	−2.22	−1.56	−1.08	−1.08	−1.3	−1.23	−1.5	−2.12	−1.44	−1.16
P	−1.6	−2.12	5.03[a]	−1.6	−0.01	−1.11	−1.34	−1.26	−1.54	−2.17	7.92[a]	−1.19
Q	−1.68	−2.22	-2.38	9.1[a]	−1.16	−1.16	−1.4	−1.32	7.95[a]	−2.27	−1.54	−1.24
W	-1.18	−1.56	−1.68	−1.18	−0.82	−0.82	−0.99	2.78[a]	−1.14	7.15[a]	−1.09	−0.88
S	−0.82	-1.08	−1.16	−0.82	−0.57	12.92[a]	−0.68	−0.65	−0.79	−1.11	−0.75	−0.61
M	−0.82	−1.08	−1.16	−0.82	−0.57	−0.57	9.08[a]	−0.65	−0.79	−1.11	0.74	−0.61
E	−0.99	−1.3	5.8[a]	−0.99	−0.68	−0.68	−0.82	0.67	0.27	−1.34	−0.91	−0.73
C	−0.93	−1.23	4.35[a]	−0.93	−0.65	−0.65	3.55[a]	−0.74	−0.9	−1.26	−0.86	−0.69
V	−1.14	−1.5	−1.61	−1.14	−0.79	−0.79	−0.95	−0.9	−1.09	9.16[a]	−1.04	−0.84
L	12.44[a]	−1.62	−1.74	−1.23	−0.85	−0.85	−1.02	−0.97	−1.18	−1.66	−1.13	0.36
A	−1.09	−1.44	−1.54	−1.09	−0.75	−0.75	−0.91	5.78[a]	−1.04	−1.47	−1	9.01[a]
T	−0.82	−1.08	−1.16	-0.82	11[a]	−0.57	0.95	−0.65	−0.79	−1.11	−0.75	−0.61

[a]Z-score > 1.96.

behavior. The P → Q path suggests that task planning (P) followed by correct quiz responses (Q) represents effective execution. In contrast, Q → W implies that despite providing correct answers (Q), nursing students may subsequently make errors (W), possibly due to task complexity or misleading elements. The sequence S → M → E → C reflects a classic self-regulation pattern involving self-monitoring (S), strategy use (M), exploration (E), and help-seeking (C). The transitions M → C and E → C suggest that learners often consult metaverse-based guides (C) after employing strategies (M) or exploring the environment (E), which indicates adaptive support-seeking behavior. Meanwhile, the V → L path demonstrates that successful task completion (V) is frequently followed by session termination (L). Collectively, these patterns underscore the cyclical, exploratory, and self-regulating nature of learning behaviors, which highlight the dynamic processes that support critical thinking awareness in immersive learning environments.

Tables 9 and 10 are graphically represented in Figure 7 to support further analysis. High-achieving nursing students were observed to closely follow the intended progression of the learning scenarios. Sequential behavior analysis allowed for

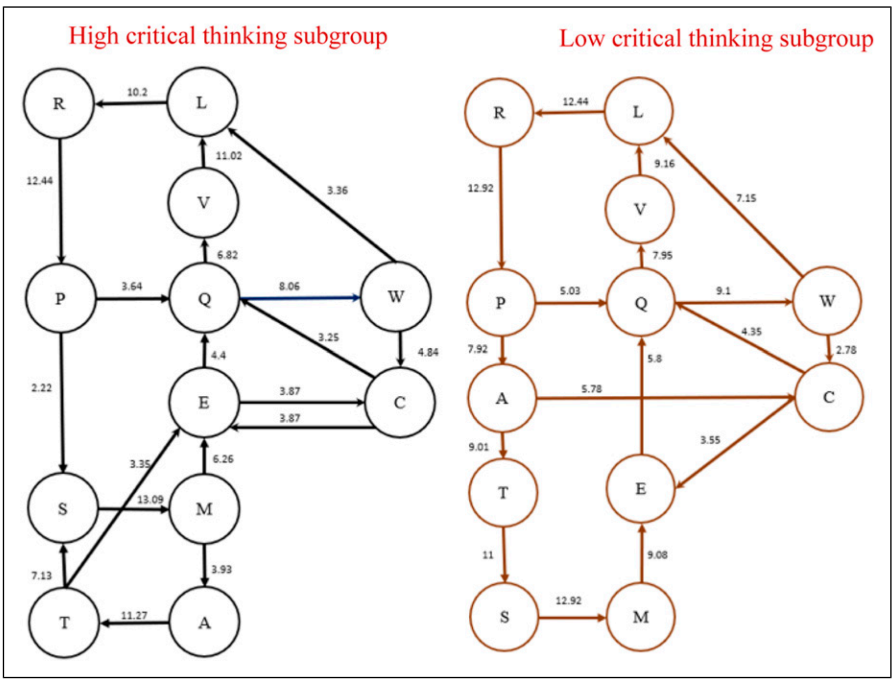

Figure 7. Learning behavior paths of the high and low critical thinking awareness nursing students in the experimental group.

A: Avoiding tasks (e.g., skipping or quitting mid-task); C: Consulting VR guides; E: Exploring VR learning environments; L: Logging out or session completion; M: Managing learning strategies; P: Planning learning tasks; Q: Answering the VR quiz correctly; R: Reading learning content; S: Self-monitoring progress; T: Time management; V: VR task success; W: Wrong answer investigation into the decision-making and behavioral patterns of nursing students with high levels of critical thinking awareness, who exhibited a highly reflective and structured decision-making process. Following the commencement of the activity, several significant learning patterns emerged. Positive sequences, such as reading content followed by task planning (R → P, Z = 12.44) and task planning followed by correct responses (P → Q, Z = 3.64), indicate effective cognitive engagement. Advanced self-regulatory behaviors reflect mature and intentional learning strategies, which were evident in behavior chains such as self-monitoring → strategy use → exploration → guide consultation (S → M, Z = 13.09; E → C, Z = 3.87). Furthermore, nursing students who experienced session interruptions demonstrated re-engagement behaviors, as shown by the sequence L → R (Z = 10.2). These findings emphasize the importance of fostering metacognitive regulation, promoting strategic help-seeking, and supporting learners who display patterns of avoidance or recurring errors within immersive learning environments.

Students with lower critical thinking awareness followed learning patterns marked by frequent repetition and heavier dependence on external feedback. While they generally completed the learning cycle, their ability to integrate strategies, make effective decisions, and adapt through self-regulation was noticeably less developed compared to peers with higher critical thinking awareness. For example, a core learning cycle beginning with reading learning content and progressing through planning and task execution was identified (R → P, Z = 12.92; P → Q, Z = 5.03), which ultimately leads to VR task success and session completion (Q → V, Z = 7.95; V → L, Z = 9.16), followed by re-engagement behaviors (L → R, Z = 12.44). High-level self-regulatory behaviors were evident in sequences such as self-monitoring followed by strategy management and exploration (S → M, Z = 12.92; M → E, Z = 9.08), with further transitions into assessment or support-seeking actions (E → Q, Z = 5.8). Additionally, error correction patterns (Q → W, Z = 9.1; W → C, Z = 2.78) and help-seeking behaviors (C → Q, Z = 4.35) were observed. Notably, learners demonstrating avoidance behaviors (A → T, Z = 9.01; A → E, Z = 5.78) often followed up with time management and re-engagement efforts (T → S, Z = 11.0), which indicates compensatory self-regulation. These findings highlight the dynamic, cyclical, and adaptive nature of learning in immersive environments, while emphasizing the importance of metacognitive support, error recovery mechanisms, and strategic help-seeking within the design of metaverse-based instructional interventions.

Discussion

This study introduced a self-regulated learning instructional strategy within a metaverse-based environment and showed significantly higher adjusted posttest learning achievement, self-efficacy, and critical thinking awareness for the experimental instructional method than for the conventional video-based method. Furthermore, exploratory analysis of the experimental group identified different behavioral sequence patterns among learners with higher and lower critical thinking awareness. Taken together, these findings contribute to the growing evidence base suggesting the potential pedagogical value of the integrated immersive, self-regulated learning method in nursing education.

The higher adjusted posttest learning achievement observed in the experimental group compared with the control group align with an expanding body of literature indicating that interactive, student-centered game-based learning environments can effectively foster learner motivation and engagement, thereby leading to enhanced academic performance, especially in emotionally supportive and stimulating learning contexts (Chang et al., 2024). Learning frameworks that incorporate metaverse-based self-regulated learning techniques have proven beneficial in improving nursing students' academic success during gamified educational tasks (Chang et al., 2025). Based on the theoretical foundation of self-regulated learning, the findings of this study are consistent with those of Freires et al. (2026) and Wang et al. (2025), suggesting that immersive digital environments can promote learner agency by encouraging meaningful interaction with learning materials and the application of knowledge in realistic, practice-oriented settings. This approach facilitates deeper conceptual understanding while reinforcing the practical relevance of acquired knowledge (Lyu & Park, 2024). In line with these principles, the present findings indicate that the integrated metaverse-based SRL instructional method was associated with higher adjusted posttest learning achievement than the conventional instructional method. The method emphasizes learner autonomy, timely feedback, and contextually grounded learning scenarios, which may support nursing students in navigating complex learning demands and preparing for practice-oriented challenges.

After adjustment for pretest scores, students in the experimental group had significantly higher posttest learning self-efficacy than those in the control group. Existing literature indicates that learning experiences in metaverse environments can enhance nursing students' motivation and engagement, which are key contributors for better academic outcomes, especially in tasks requiring critical thinking and problem-solving (Parrales-Bravo et al., 2026). Furthermore, Hsu (2026) demonstrated that the integration of self-regulated learning strategies within metaverse-based settings can boost students' confidence and perceived competence during class activities. According to Shen et al. (2025), integrating self-regulated learning techniques into teaching practices significantly strengthens learners' beliefs in their own abilities. These instructional models promote meaningful interaction with content and encourage knowledge application in authentic contexts, such as dietary planning simulations for cancer prevention, thereby enhancing nursing students' conceptual understanding and reinforcing the real-world significance of the learning process (Chang et al., 2024). The current findings indicate that the integrated metaverse-based SRL approach was associated with higher adjusted posttest self-efficacy than the conventional instructional approach. By encouraging independence, offering immediate feedback, and situating learning within contextually rich scenarios, these instructional features may have supported students' confidence when managing complex educational challenges.

For critical thinking awareness, the ANCOVA indicated a significant adjusted posttest difference between the two instructional methods. Conventional classroom settings often rely on generalized feedback that addresses groups rather than the specific needs of individual learners, which can limit access to personalized support. In contrast, metaverse-based learning environments allow for the timely and context-sensitive delivery of instructional materials and guidance, embedded directly within authentic learning scenarios rather than being detached from real-world learning challenges (Chang et al., 2025; Chen, 2026). According to the cognitive framework proposed by Yang and Kang (2022), synchronizing learning content with the learner's problem-solving process both in timing and in situational contexts significantly facilitates the development of critical thinking awareness. This alignment may further account for the enhanced engagement and learning outcomes observed in the present study. Supporting this, Amin et al. (2025) found that embedding instructional tools within immersive digital environments contributed meaningfully to improved academic performance. Immersive technologies have been found to enhance not only knowledge but also higher-order thinking skills (Li et al., 2021). Specifically, Singh et al. (2024) reported that engaging learners in tasks requiring both knowledge acquisition and application within metaverse environments led to significant improvements in critical thinking awareness. Therefore, when implemented thoughtfully, such platforms do more than facilitate instructional content, they also promote individualized, adaptive learning experiences. Consistent with these findings, the present study found significantly higher adjusted posttest critical thinking awareness in the experimental group than in the control group; this between-group difference should not be interpreted as evidence of improvement within each group or as an isolated causal effect of metaverse technology or SRL.

The behavioral patterns of nursing students engaged in metaverse-based self-regulated learning were examined with a specific focus on the association between critical thinking awareness and interaction sequences. Exploratory differences in learning trajectories, decision-making strategies, and adaptive behaviors were observed after participants were categorized into higher and lower critical thinking awareness groups. Students with high critical thinking awareness demonstrated a more reflective and structured approach to learning. They consistently followed effective self-regulated learning patterns, such as transitioning from reading to task planning (R → P) and executing tasks correctly (P → Q). Their engagement in metacognitive behaviors such as self-monitoring (S), managing strategies (M), exploring resources (E), and consulting guides (C) highlights their capacity to regulate learning autonomously. Importantly, sequences such as S → M → E → C suggest a mature and intentional learning approach that aligns with Zimmerman's self-regulated learning framework, in which learners iteratively cycle through forethought, performance, and self-reflection phases.

In contrast, nursing students with lower critical thinking awareness exhibited more repetitive and feedback-dependent behaviors. Although they completed learning cycles (e.g., R → P → Q → V → L), their behaviors were characterized by error-prone decision-making and greater reliance on external support. Help-seeking behaviors aimed at correcting incorrect responses (e.g., W → C, C → Q) and compensatory regulation strategies (e.g., A → T → S) were more frequently observed, indicating a reactive rather than proactive approach to learning challenges. These exploratory subgroup differences suggest an association between critical thinking awareness and behavioral sequence patterns.

Within the experimental group, the observed behavioral sequences reflected dynamic and cyclical learning processes and suggested individual differences in how learners navigated complexity and uncertainty. Because behavioral data were analyzed only for the experimental group, these exploratory patterns cannot establish that the immersive environment caused the observed behaviors. These findings underscore the need to design metaverse-based self-regulated learning interventions that incorporate adaptive scaffolding tailored to learners' metacognitive readiness (Bandura, 1978). Providing timely guidance, embedded feedback, and structured pathways for strategic support-seeking may help bridge the gap for nursing students with lower self-regulatory capacity or critical thinking awareness (Liu, Chan, & Hou, 2025). These results are consistent with Chu et al. (2025), further suggesting that visualizing behavioral sequences through lag sequential analysis can offer granular insights into how learners interact with immersive content. This approach not only helps identify effective learning paths but also pinpoints opportunities for where instructional design can prevent disengagement or reinforce productive behaviors.

In summary, exploratory behavioral analyses suggested that students with higher critical thinking awareness showed more autonomous and structured engagement, whereas those with lower critical thinking awareness showed more feedback-dependent patterns and may benefit from targeted scaffolding. These implications are crucial for educators and instructional designers seeking to enhance the effectiveness and equity of technology-enhanced learning experiences. Future research should further investigate how adaptive scaffolding mechanisms can be systematically integrated into metaverse-based platforms to optimize learning outcomes across diverse learner profiles.

Limitations of the Present Study

Several limitations of this study should be considered. First, participants were exclusively drawn from one introductory cancer prevention nutrition course at a single university, which may limit the broader applicability of the findings across different educational systems and cultural settings. Future research should enhance generalizability by recruiting a more diverse sample across multiple institutions and demographic contexts. Second, the nonrandom quasi-experimental design limits causal inference. The two conditions differed simultaneously in technology, immersion, interactivity, AI support, gamification, feedback, and SRL scaffolding; therefore, the findings support comparison of the two instructional methods as a whole rather than causal claims about the isolated effect of metaverse technology or SRL. Future studies should use randomized or factorial/component-based designs to better isolate the contribution of individual instructional features. In addition, because participants had no prior experience with metaverse-based learning environments before the intervention, a potential novelty effect may have influenced their engagement levels and learning responses. Future studies should examine whether the observed effects can be sustained after learners become more familiar with immersive virtual learning environments.

An additional limitation lies in the study's emphasis on short-term learning outcomes, leaving the sustained impact of the metaverse-based self-regulated learning model unaddressed. Future longitudinal studies are needed to explore how this instructional approach, when integrated with other teaching strategies, supports the long-term development of essential competencies such as domain-specific knowledge and hands-on abilities. While this study concentrated on immediate outcomes such as learning achievement, learning self-efficacy, and critical thinking awareness, further research is warranted to investigate the potential extended benefits related to knowledge and skill acquisition. Moreover, it would be valuable to conduct more in-depth analyses of the learning behaviors exhibited by nursing students with lower levels of critical thinking awareness to inform the design of more refined self-regulated learning frameworks and more targeted scaffolding techniques. Furthermore, although the present study primarily relied on quantitative measures, incorporating semi-structured interviews or other qualitative approaches in future research could provide deeper insights into students' learning experiences, perceptions, and self-regulated learning processes, thereby complementing and strengthening the interpretation of the quantitative findings.

The exploratory behavioral analysis used a median split, resulting in small subgroups. This approach may reduce information and produce unstable subgroup patterns; therefore, these findings should be interpreted cautiously as exploratory. Future studies with larger samples should retain critical thinking awareness as a continuous variable or use more robust analytical approaches to examine its association with behavioral patterns. Overcoming these limitations in future studies can further amplify the impact of metaverse-based instructional strategies on cancer prevention dietary education. This would not only enrich this methods' effectiveness within existing educational frameworks but also facilitate broader adoption across diverse cancer-prevention dietary programs. Ultimately, such advancements could reinforce the core structure of professional training in cancer prevention nutrition and related healthcare fields.

Conclusion

The findings indicate that the integrated metaverse-based self-regulated learning instructional method was associated with higher adjusted posttest learning achievement than conventional video-based instruction in cancer prevention dietary education. The immersive environment provided interactive scenarios, timely feedback, and opportunities for targeted instructional support; however, the present study did not directly evaluate personalization or adaptive resource allocation. Accordingly, these features should be regarded as design possibilities rather than demonstrated effects of the intervention.

After controlling for pretest scores, the experimental group showed higher adjusted posttest learning achievement, self-efficacy, and critical thinking awareness than the control group. Because group assignment was nonrandom and the instructional methods differed across multiple components, these between-group differences should not be interpreted as evidence of the isolated causal efficacy of metaverse technology or SRL. The exploratory behavioral analysis further showed different sequential patterns between students with higher and lower critical thinking awareness, suggesting possible differences in how learners engaged with the integrated learning environment.

Overall, the findings suggest that integrating immersive learning activities with SRL-oriented supports may be a promising instructional approach for nursing and health education. However, personalization, adaptability, and scalability were not directly evaluated and therefore require further investigation before broader claims can be made.

The main contribution of this study lies in examining an integrated metaverse-based SRL instructional method in cancer prevention dietary education and comparing its outcomes with conventional 2D video instruction. The study also provides exploratory process-level evidence from behavioral learning analytics. Its key contributions include:

(1) Providing context-rich immersive learning experiences in which nursing students engaged with cancer-prevention dietary scenarios.
(2) Exploring differences in behavioral sequence patterns between learners with higher and lower critical thinking awareness, offering process-level insights into self-regulated learning behaviors in the immersive environment.
(3) Applying lag sequential analysis to examine transitions among learning behaviors, complementing frequency- or time-based indicators; LSA is an established analytical method rather than a novel methodological contribution of this study.
(4) Suggesting the potential value of embedded feedback and metacognitive scaffolding for supporting learners with different learning needs, while recognizing that adaptive support was not independently evaluated.

In conclusion, the study provides preliminary evidence supporting further investigation of integrated immersive and SRL-oriented instructional methods in nursing and health education. Replication with randomized designs, larger samples, and direct evaluation of personalization, adaptability, and scalability is needed to establish the robustness and generalizability of these findings.

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Ethical Considerations

This study was approved by the Research Ethics Committee of Taipei Medical University under the full board review process of the TMU-Joint Institutional Review Board on 07/12/2021. The ethics protocol remained valid from 08/12/2021 until 07/12/2022. Accordingly, the experimental procedures and participant recruitment implemented in this research were during this time, while the five-week instructional intervention started from 01/09/2022, and hence finished within the timeframe of ethical approval.

Consent for Publication

The publication of this study has been approved by all authors.

Author Contributions

Conceptualisation and study design were undertaken collaboratively by the authors. Material preparation, data collection, and data analysis were performed by Ching-Yi Chang. Methodology development and academic supervision were provided by Husni Mubarok and Pei-Yu Cheng. The first draft of the manuscript was prepared by Ching-Yi Chang and Pei-Yu Cheng. Jordan Allison contributed to the critical review and scholarly revision of the manuscript, including editing, refinement of the argumentation, and improvement of the presentation of the study. All authors commented on previous versions of the manuscript and approved the final version.

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Declaration of Conflicting Interests

The authors declare the following potential conflict of interest with respect to the research, authorship, and/or publication of this article. One of the authors, Dr. Jordan Allison, serves as Editor-in-Chief of the Journal of Educational Computing Research. Consistent with the journal's conflict of interest policy and recommendations from the Committee on Publication Ethics regarding submissions from editors, editorial responsibility for this manuscript was delegated to an independent editor with full authority over the peer review and editorial decision-making process. Dr. Allison had no involvement in the peer review process, editorial evaluation, reviewer selection, or final decision regarding this manuscript, and had no access to reviewer reports during the evaluation process.

References

Aljumaie, M., Chi Nguyen, H., Chu, N. H., Nguyen, C. T., Nguyen, D. N., Thai Hoang, D., & Dutkiewicz, E. (2023). Potential applications and benefits of metaverse. In *Metaverse communication and computing networks: Applications, technologies, and approaches* (pp. 17–37). Wiley. https://doi.org/10.1002/9781394160013.ch2

Amin, S. M., Atta, M. H. R., Abd Elmoaty, A. E. E., Ismail, H. A., Kotp, M. H., Basyouny, H. A. A., & El-Sayed, A. A. I. (2025). Bridging virtual and real learning: The role of digital literacy and metaverse perspectives in enhancing academic motivation in nursing education. *BMC Nursing*, *24*(1), 1113. https://doi.org/10.1186/s12912-025-03681-x

Ashour, O., Alkhatib, A. M., Al Zureikat, Q., Al-Shaikhli, M., Ata, B. B., Massad, T., Al-Ani, A., & Al-Sabbagh, M. Q. (2023). Investigating medical students' satisfaction towards video-based learning versus face-to-face lectures: A Jordanian tertiary teaching hospital experience. *Korean Journal of Medical Education*, *35*(1), 21–32. https://doi.org/10.3946/kjme.2023.246

Asiksoy, G. (2023). Empirical studies on the metaverse-based education: A systematic review. *International Journal of Engineering Pedagogy*, *13*(3), 120–133. https://doi.org/10.3991/ijep.v13i3.36227

Bakeman, R., & Gottman, J. M. (1997). *Observing interaction: An introduction to sequential analysis* (2nd ed.). Cambridge University Press.

Bakeman, R., & Quera, V. (1995). *Analyzing interaction: Sequential analysis with SDIS & GSEQ*. Cambridge University Press.

Bandura, A. (1978). Reflections on self-efficacy. *Advances in Behaviour Research and Therapy*, *1*(4), 237–269. https://doi.org/10.1016/0146-6402(78)90002-7

Barak, M., & Shahab, C. (2023). The conceptualization of critical thinking: Toward a culturally inclusive framework for technology-enhanced instruction in higher education. *Journal of Science Education and Technology*, *32*(6), 872–883. https://doi.org/10.1007/s10956-022-09999-4

Chang, C. Y., Li, C. H., & Hwang, G. J. (2025). Metaverse-integrated scenario-based professional training based on the social learning theory: Evidence from achievement, critical thinking, decision-making performance, and behavioral analysis. *Journal of Educational Computing Research*, *64*(5), 07356331261424218. https://doi.org/10.1177/07356331261424218

Chang, C. Y., Setiani, I., Darmawansah, D., & Yang, J. C. (2024). Effects of game-based learning integrated with the self-regulated learning strategy on nursing students' entrustable professional activities: A quasi-experimental study. *Nurse Education Today*, *139*, 106213. https://doi.org/10.1016/j.nedt.2024.106213

Chang, S. C., & Dao, N. D. (2025). An intelligent recommender system based on K-nearest neighbors to foster self-regulated learning and reduce cognitive load in online higher education. *Computers & Education*, *240*, 105470. https://doi.org/10.1016/j.compedu.2025.105470

Chen, X., Zou, D., Xie, H., & Wang, F. L. (2023). Metaverse in education: Contributors, cooperations, and research themes. *IEEE Transactions on Learning Technologies*, *16*(6), 1111–1129. https://doi.org/10.1109/TLT.2022.3191801

Chen, Y. C. (2026). Exploring the impact of metaverse-integrated blended learning on Mandarin directional and positional expressions. *Computer Assisted Language Learning*, 1–35. https://doi.org/10.1080/09588221.2026.2628942

Cho, I. Y., Yun, J. Y., & Moon, S. H. (2024). Development and effectiveness of a metaverse reality-based family-centered handoff education program in nursing students. *Journal of Pediatric Nursing*, *76*, 176–191. https://doi.org/10.1016/j.pedn.2024.02.005

Chou, Y. S., Hou, H. T., Chang, K. E., & Su, C. L. (2023). Designing cognitive-based game mechanisms for mobile educational games to promote cognitive thinking: An analysis of flow state and game-based learning behavioral patterns. *Interactive Learning Environments*, *31*(5), 3285–3302. https://doi.org/10.1080/10494820.2021.1926287.

Chu, X., Wang, M., Spector, J. M., Chen, N. S., Chai, C. S., Hwang, G. J., & Zhai, X. (2025). Enhancing the flipped classroom model with generative AI and Metaverse technologies: Insights from lag sequential and epistemic network analysis. *Educational Technology Research and Development*, *73*, 1–29. https://doi.org/10.1007/s11423-025-10457-2

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Freires, T., Oliveira, A., Pinto, D., & Torres, A. C. (2026). Teacher agency in curriculum and pedagogical development: Reflections from a design research project about self-regulated learning in secondary schools. *Curriculum Journal*, *37*(2), 422–442. https://doi.org/10.1002/curj.70010

Goh, T. T. (2026). Learning management system log analytics: The role of persistence and consistency of engagement behaviour on academic success. *Journal of Computers in Education*, *13*(1), 283–306. https://doi.org/10.1007/s40692-025-00358-x

Hsiao, H. S., Chang, Y. C., Lin, K. Y., Chen, J. C., Lin, C. Y., Chung, G. H., & Chen, J. H. (2023). Applying the design thinking model to hands-on mechatronics STEM activities for senior high school students to improve the learning performance and learning behavior. *International Journal of Technology and Design Education*, *33*(4), 1389–1408. https://doi.org/10.1007/s10798-022-09778-7

Hsu, C. L. (2026). Unlocking determinants influencing intention to use metaverse technology: An integration of self-determination theory and UTAUT2. *Journal of Hospitality and Tourism Technology*, 1–22. https://doi.org/10.1108/JHTT-10-2024-0663

Hwang, G. J., & Chien, S. Y. (2024). Broad sense and narrow sense perspectives on the metaverse in education: Roles of virtual reality, augmented reality, artificial intelligence and pedagogical theories. *International Journal of Mobile Learning and Organisation*, *18*(1), 1–14. https://doi.org/10.1504/IJMLO.2024.135179

Jeon, H., Shin, H., & Woo, J. (2024). User experience and interface assessment for metaverse platforms on nurses and nursing students: A cross-sectional study. *Nurse Education Today*, *139*, 106222. https://doi.org/10.1016/j.nedt.2024.106222

Kesuma, A. T., Harun, Z., Putranta, H., & Kistoro, H. C. A. (2020). Evaluation of the self-regulated learning model in high schools: A systematic literature review. *Universal Journal of Educational Research*, *8*(10), 4792–4806. https://doi.org/10.13189/ujer.2020.081051

Khiri, N., & Howells, K. (2025). Nutritional education in medical curricula and clinical practice: A scoping review on the knowledge deficit amongst medical students and doctors. *Journal of Human Nutrition and Dietetics*, *38*(2), e70031. https://doi.org/10.1111/jhn.70031

Kim, Y., & Kim, M. Y. (2023). Effects of metaverse-based career mentoring for nursing students: A mixed methods study. *BMC Nursing*, *22*(1), 160. https://doi.org/10.1186/s12912-023-01323-8

Klein-Latucha, O., & Hershkovitz, A. (2024). When leaving is persisting: Studying patterns of persistence in an online game-based learning environment for mathematics. *Journal of Learning Analytics*, *11*(2), 42–51. https://doi.org/10.18608/jla.2023.8219

Kurylo, V., Karaman, O., Bader, S., Pochinkova, M., & Stepanenko, V. (2023). Critical thinking as an information security factor in the modern world. *Social and Legal Studios*, *3*(6), 67–74. https://doi.org/10.32518/sals3.2023.67

Lavrakas, P. (2008). *Encyclopedia of survey research methods, Sage Publications*. Sage Publications Inc.

Li, F. Y., Hwang, G. J., Chen, P. Y., & Lin, Y. J. (2021). Effects of a concept mapping-based two-tier test strategy on students' digital game-based learning performances and behavioral patterns. *Computers & Education*, *173*, 104293. https://doi.org/10.1016/j.compedu.2021.104293

Lin, H. C., Hwang, G. J., & Hsu, Y. D. (2019). Effects of ASQ-based flipped learning on nurse practitioner learners' nursing skills, learning achievement and learning perceptions. *Computers & Education*, *139*, 207–221. https://doi.org/10.1016/j.compedu.2019.05.014

Liu, J., Shadiev, R., & Cao, M. (2025). Effects of digital citizenship educational game on teenagers' learning achievement, motivation, cognitive load, and behavioral patterns. *Education and Information Technologies*, *30*, 1–54. https://doi.org/10.1007/s10639-025-13399-7

Liu, S. W., Chan, H. Y., & Hou, H. T. (2025). Role-playing monument exploration: An online educational game with a role-playing mechanism and multi-dimensional scaffolding for monument tours. *Educational Technology Research and Development*, *73*, 1–25. https://doi.org/10.1007/s11423-025-10480-3

Lyu, Z., & Park, K. (2024). The effect of self-regulation and metaverse features on generation Z's adoption of gamified learning platforms. *International Journal of Human-Computer Interaction*, *41*(15), 9209–9223. https://doi.org/10.1080/10447318.2024.2423338

Muthmainnah, M., Cardoso, L., Marzuki, A. G., & Al Yakin, A. (2025). A new innovative metaverse ecosystem: VR-based human interaction enhances EFL learners' transferable skills. *Discover Sustainability*, *6*(1), 156. https://doi.org/10.1007/s43621-025-00913-7

Navarrete, E., Nehring, A., Schanze, S., Ewerth, R., & Hoppe, A. (2025). A closer look into recent video-based learning research: A comprehensive review of video characteristics, tools, technologies, and learning effectiveness. *International Journal of Artificial Intelligence in Education*, *35*(4), 1631–1694. https://doi.org/10.1007/s40593-025-00481-x

Ngulube, P., & Ncube, M. M. (2025). Leveraging learning analytics to improve the user experience of learning management systems in higher education institutions. *Information*, *16*(5), 419. https://doi.org/10.3390/info16050419

Nouira, A., Cheniti-Belcadhi, L., & Braham, R. (2019). An ontology-based framework of assessment analytics for massive learning. *Computer Applications in Engineering Education*, *27*(6), 1343–1360. https://doi.org/10.1002/cae.22155.

Pansri, B., Sharma, S., Timilsina, S., Choonhapong, W., Kurashige, K., Watanabe, S., & Sato, K. (2024). Understanding student learning behavior: Integrating the self-regulated learning approach and k-means clustering. *Education Sciences*, *14*(12), 1291. https://doi.org/10.3390/educsci14121291

Parrales-Bravo, F., Tolozano-Benites, R., Jadán-Guerrero, J., Vasquez-Cevallos, L., & Gómez-Rodríguez, V. (2026). From virtual worlds to real-world equity: A scoping review of the metaverse as computer-assisted learning for STEM competencies. *Computers*, *15*(4), 229. https://doi.org/10.3390/computers15040229

Perez-Garcia, I. N., Andrade-Gómez, E., Arias-Colinas, M., & Pardavila-Belio, M. I. (2025). Exploring nutritional education in undergraduate nursing students: A scoping review. *Nurse Education in Practice*, *90*, 104623. https://doi.org/10.1016/j.nepr.2025.104623

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). A manual for the use of the motivated strategies for learning questionnaire (MSLQ). MI: National center for research to improve postsecondary teaching and learning. (ERIC Document Reproduction Service. No. ED 338122).

Rahimi, R. A., & Oh, G. S. (2024). Rethinking the role of educators in the 21st century: Navigating globalization, technology, and pandemics. *Journal of Marketing Analytics*, *12*(2), 182–197. https://doi.org/10.1057/s41270-024-00303-4

Rebelo Marcolino, M., Reis Porto, T., Thompsen Primo, T., Targino, R., Ramos, V., Marques Queiroga, E., & Cechinel, C. (2025). Student dropout prediction through machine learning optimization: Insights from moodle log data. *Scientific Reports*, *15*(1), 9840. https://doi.org/10.1038/s41598-025-93918-1

Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *Wiley Interdisciplinary Reviews*, *10*(3), Article e1355. https://doi.org/10.1002/widm.1355

Shen, B., Weng, F., Jiang, M. Y. C., Zou, D., & Jong, M. S. Y. (2025). Harnessing spherical video-based virtual reality to enhance EFL learners' writing performance and self-regulated learning strategy use. *Computer Assisted Language Learning*, *39*(5-6), 1–46. https://doi.org/10.1080/09588221.2025.2482148

Singh, M., Sun, D., & Zheng, Z. (2024). Enhancing university students' learning performance in a metaverse-enabled immersive learning environment for STEM education: A community of inquiry approach. *Future in Educational Research*, *2*(3), 288–309. https://doi.org/10.1002/fer3.56

Thornhill-Miller, B., Camarda, A., Mercier, M., Burkhardt, J. M., Morisseau, T., Bourgeois-Bougrine, S., Lubart, T., El Hayek, S., Augereau-Landais, M., Mourey, F., Feybesse, C., & Sundquist, D. (2023). Creativity, critical thinking, communication, and collaboration: Assessment, certification, and promotion of 21st century skills for the future of work and education. *Journal of Intelligence*, *11*(3), 54. https://doi.org/10.3390/jintelligence11030054

von Kotzebue, L., Zumbach, J., & Brandlmayr, A. (2022). Digital escape rooms as game-based learning environments: A study in sex education. *Multimodal Technologies and Interaction*, *6*(2), 8. https://doi.org/10.3390/mti6020008

Wang, C., Chen, X., Li, Y., Wang, P., Wang, H., & Li, Y. (2025). MetaClassroom: A new paradigm and experience for programming education. *Journal of Educational Computing Research*, *63*(4), 864–901. https://doi.org/10.1177/07356331251322470

Wang, J. (2024). Promoting the application of metaverse technology in practical teaching for university: An identification and evaluation of barriers. *International Journal of Human-Computer Interaction*, *41*(16), 1–19. https://doi.org/10.1080/10447318.2024.2430427

Wang, M., Yu, H., Bell, Z., & Chu, X. (2022). Constructing an edu-metaverse ecosystem: A new and innovative framework. *IEEE Transactions on Learning Technologies*, *15*(6), 685–696. https://doi.org/10.1109/TLT.2022.3210828.

Wang, Q., Mousavi, A., Lu, C., & Gao, Y. (2023). Examining adults' behavioral patterns in a sequence of problem solving tasks in technology-rich environments. *Computers in Human Behavior*, *147*, Article 107852. https://doi.org/10.1016/j.chb.2023.107852

Wilt, J. K., & Thomson, M. D. (2025). "If I Start [Primary Prevention] Now, I can prevent [Cancer]": College students endorse cancer prevention education. *Journal of Cancer Education*, *40*(5), 783–791. https://doi.org/10.1007/s13187-025-02574-6

Yang, S. Y., & Kang, M. K. (2022). Efficacy testing of a multi-access metaverse-based early onset schizophrenia nursing simulation program: A quasi-experimental study. *International Journal of Environmental Research and Public Health*, *20*(1), 449. https://doi.org/10.3390/ijerph20010449

Youssef, N. H., & Alibraheim, E. A. (2024). Self-regulated learning strategies among graduate students and their relationship with statistics anxiety. *Education Sciences*, *15*(1), 17. https://doi.org/10.3390/educsci15010017

Zeng, B. (2024). Visual interactive Mobile analysis of online English learning behavior based on lagged sequence analysis approach. *International Journal of Interactive Mobile Technologies*, *18*(10), 34–47. https://doi.org/10.3991/ijim.v18i10.49035

Zhao, Z., Zhao, B., Ji, Z., & Liang, Z. (2022). On the personalized learning space in educational metaverse based on heart rate signal. *International Journal of Information and Communication Technology Education*, *18*(2), 1–12. https://doi.org/10.4018/ijicte.314565

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, *25*(1), 3–17. https://doi.org/10.1207/s15326985ep2501_2

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Appendix

Learning Achievement for Pretest

No.	Scenario question	Options	Answer	Rationale
1	In the learning environment, students are asked to select a meal that may reduce the risk of colorectal cancer. Which option is most appropriate?	A. Sausage with white bread B. Brown rice with steamed vegetables C. Fried chicken with fries D. Cream-based pasta	B	Whole grains and vegetables provide dietary fiber, which is associated with a lower risk of colorectal cancer.
2	In the learning environment, students must recommend a healthier protein alternative to reduce cancer risk associated with processed meats. Which option is the best choice?	A. Bacon B. Ham C. Grilled salmon D. Hot dog	C	Processed meats are linked to increased cancer risk, while fish provides healthier protein and omega-3 fatty acids.
3	In the learning environment, students must choose foods rich in antioxidants for cancer prevention. Which option is most appropriate?	A. Dark green vegetables B. Refined white rice C. Butter cake D. Sugary drinks	A	Dark green vegetables contain antioxidant compounds such as beta-carotene and vitamins that support cancer prevention.
4	In the learning environment, students evaluate dietary strategies that may reduce gastric cancer risk. Which option is most appropriate?	A. Consuming more pickled foods B. Reducing high-salt foods C. Drinking sugary beverages D. Increasing processed meat intake	B	High salt intake and preserved foods are associated with increased gastric cancer risk.
5	In the learning environment, students must choose the cooking method that minimizes the formation of carcinogenic compounds. Which option is most appropriate?	A. Charbroiling B. Deep frying C. Steaming D. Barbecue grilling	C	Steaming produces fewer carcinogenic compounds compared with high-temperature cooking methods such as grilling or frying.

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No.	Scenario question	Options	Answer	Rationale
6	In the learning environment, students must select foods rich in phytochemicals that may support cancer prevention. Which option is most appropriate?	A. Cruciferous vegetables B. Candy C. White bread D. Processed snacks	A	Cruciferous vegetables contain compounds such as sulforaphane that may contribute to cancer prevention.
7	In the learning environment, students evaluate food safety factors associated with liver cancer prevention. Which option is the safest choice?	A. Moldy peanuts B. Fresh nuts C. Spoiled fermented soy products D. Moldy grains	B	Moldy foods may contain aflatoxins, which are strongly associated with liver cancer risk.
8	In the learning environment, students select foods rich in protective phytochemicals that may contribute to reducing cancer risk. Which option is most appropriate?	A. High-fat red meat B. Dark-colored fruits C. Processed meats D. Sugary beverages	B	Fruits contain antioxidants and phytochemicals that may reduce cancer risk.
9	In the learning environment, students must identify a dietary pattern consistent with cancer prevention guidelines. Which option is most appropriate?	A. High intake of processed foods B. Diet rich in fruits, vegetables, and whole grains C. High-fat diet D. High-sugar diet	B	Diets rich in plant-based foods are associated with lower cancer risk.
10	In the learning environment, students identify a key dietary principle for overall cancer prevention. Which option is most appropriate?	A. High-calorie diet B. Plant-based dietary pattern C. Sugary drinks D. Ultra-processed foods	B	A plant-based dietary pattern emphasizes fruits, vegetables, legumes, and whole grains, which support cancer prevention.

Learning Achievement for Posttest

No.	Scenario question	Options	Answer	Rationale
1	In the learning environment, students must select a breakfast that aligns with cancer-preventive dietary recommendations. Which option is the most appropriate?	A. Whole-grain oatmeal with berries B. Sugary cereal with sweetened milk C. Butter croissant D. Fried sausage sandwich	A	Whole grains and berries provide fiber and antioxidants that support cancer prevention.
2	In the learning environment, students are asked to select a beverage that supports a cancer-preventive diet. Which option is the healthiest choice?	A. Sugar-sweetened soda B. Sweet milk tea C. Green tea D. Energy drink	C	Green tea contains polyphenols and antioxidants that may contribute to cancer prevention.
3	In the learning environment, students must identify a cooking practice that helps reduce exposure to dietary carcinogens. Which option is most appropriate?	A. Avoiding burnt or charred foods B. Increasing oil temperature during frying C. Grilling meat until heavily charred D. Using excessive cooking oil	A	Burnt or charred foods may contain carcinogenic compounds such as heterocyclic amines.
4	In the learning environment, students must choose a dietary habit that supports long-term cancer prevention. Which option is most appropriate?	A. Frequent consumption of ultra-processed foods B. Balanced intake of fruits and vegetables daily C. Skipping vegetables D. High consumption of sugary snacks	B	A diet rich in fruits and vegetables is associated with reduced cancer risk.

(continued)

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No.	Scenario question	Options	Answer	Rationale
5	In the learning environment, students evaluate meal choices that may help reduce inflammation associated with cancer risk. Which option is most appropriate?	A. Fried fast food meal B. Salad with olive oil dressing and legumes C. Processed meat sandwich D. Instant noodles	B	Legumes and healthy fats such as olive oil contribute to anti-inflammatory dietary patterns.
6	In the learning environment, students must identify a healthy snack that supports cancer prevention. Which option is most appropriate?	A. Fresh fruit with nuts B. Potato chips C. Candy bar D. Processed pastries	A	Fruits and nuts contain vitamins, minerals, and phytochemicals beneficial for cancer prevention.
7	In the learning environment, students evaluate dietary fat sources in relation to cancer prevention. Which option is most appropriate?	A. Processed meat fat B. Butter-rich foods C. Plant-based oils such as olive oil D. Trans-fat snacks	C	Plant-based oils contain healthy fats that support overall health.
8	In the learning environment, students must select a lunch that reflects evidence-based cancer prevention guidelines. Which option is most appropriate?	A. Grilled chicken salad with mixed vegetables B. Fried chicken bucket C. Processed meat pizza D. Creamy bacon pasta	A	Lean protein with vegetables supports balanced nutrition and lower cancer risk.
9	In the learning environment, students must identify a dietary practice that may help maintain healthy body weight and reduce cancer risk. Which option is most appropriate?	A. Portion control and balanced meals B. Frequent consumption of high-calorie desserts C. Large portion fast food meals D. Skipping meals and overeating later	A	Maintaining a healthy body weight is an important factor in cancer prevention.

(continued)

(continued)

No.	Scenario question	Options	Answer	Rationale
10	In the learning environment, students must identify a recommended strategy for reducing dietary cancer risk. Which option is most appropriate?	A. Increasing processed food consumption B. Emphasizing a variety of plant-based foods C. Increasing sugary beverages D. Limiting vegetable intake	B	Plant-based dietary patterns provide fiber, vitamins, and phytochemicals that support cancer prevention.

Self-Efficacy for Learning

(1) I believe I will receive an excellent grade in this activity.
(2) I'm certain I can understand the most difficult material presented in the readings for this course.
(3) I'm confident I can understand the basic concepts taught in this course.
(4) I'm confident I can understand the most complex material presented by the instructor in this course.
(5) I'm confident I can do an excellent job on the assignments and tests in this course.
(6) I expect to do well in this activity.
(7) I'm certain I can master the skills being taught in this class.
(8) Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.

Critical Thinking Awareness

(1) During the learning process, I reflect on whether what I have learned is correct.
(2) During the learning process, I evaluate the value of new information or evidence presented to me.
(3) When learning new content, I try to understand it from different perspectives.
(4) During the learning process, I evaluate different opinions to determine which one is more reasonable.
(5) During the learning process, I am able to identify which information is trustworthy.
(6) During the learning process, I distinguish facts that are supported by evidence.