Impact of Tutorial Modes with Different Time Flow Rates in Virtual Reality Games

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Virtual reality's (VR) unique affordances compared to traditional media have produced innovative interaction modes and tutorial methodologies in VR games. Existing research predominantly focuses on the performance of VR tutorial modes, such as the placement of text and diagrams within tutorial content. However, few studies have delved into other attributes of tutorials. This study categorizes 4 VR game tutorial modes based on time flow: (1) traditional instruction screen, (2) slow motion, (3) bullet time, and (4) context-sensitive mode. This paper evaluates the impact of these 4 VR game tutorial modes with varying time flow rates on controls learnability, engagement-related outcomes, and player performance. We conducted a between-subjects experiment with 59 participants. Results indicated that bullet time significantly enhanced controls learnability, reduced cognitive load, and improved player performance when compared to other tutorial modes. Our research contributes to a more comprehensive understanding of VR game tutorials and offers practical guidance for game designers, underscoring the potential of bullet time to enhance learnability and game experience.

CCS Concepts: • **Human-centered computing → Virtual reality**; **User studies**; • **Software and its engineering → Interactive games**.

Additional Key Words and Phrases: Virtual Reality, Games, Game Tutorial, User Study

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1 INTRODUCTION

The global virtual reality (VR) and augmented reality (AR) market has been expanding in recent years [Alsop 2021]. VR is increasingly finding applications across various sectors such as healthcare [Baghaei et al. 2021; Rose et al. 2018; Wang et al. 2023], manufacturing [Berg and Vance 2017; Lawson et al. 2016], training [Bertram et al. 2015; Lee et al. 2019; Monteiro et al. 2024], learning

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[Li et al. 2023; Lu et al. 2018; Monteiro et al. 2022], and numerous other areas. Among its many application areas, VR gaming has become one of VR's most prominent use cases, with a wide range of game types available for different audiences [Frommel et al. 2017; Wang et al. 2022; Xu et al. 2021a,b, 2023; Yu et al. 2023]. Just like games in traditional platforms, tutorials are usually the first element players come across when first playing games in VR [Andersen et al. 2012]. However, how to design more effective tutorials to help VR players learn game operations is largely underexplored.

Games often require tutorials to help players learn in-game operations, so designing effective tutorials is critical to attracting and retaining new players, especially in VR, because of its newer interaction mechanisms and input devices. In general, tutorials can be challenging to design [Andersen et al. 2012]. Designers of modern games often rely on intuition, personal experience, and extensive user testing to create game tutorials, and while these approaches have provided modern games with a wide variety of tutorial styles, including hints, help buttons, manuals, and interactive challenges, the relative effectiveness of these tutorial styles is unclear, particularly in VR [Andersen et al. 2012]. Compared to traditional non-VR games, VR games often employ interaction schemes that can be unfamiliar to users [Frommel et al. 2017] due to their distinctive input devices and immersive environments that are different from those of traditional games. This requires designers to create tutorials that are more tailored to VR [Tan et al. 2015].

When designing game tutorials, the game's complexity should be taken into account first, and studies have shown that the usefulness of tutorials depends heavily on the complexity of the game [Andersen et al. 2012]. For instance, investing in tutorials for games where mechanics can be discovered through experimentation, such as puzzle games, might not yield significant benefits. Research on tutorials has shown that providing context-sensitive details increases game engagement [Andersen et al. 2012], triggering higher positive emotions, lower negative emotions, and higher motivation in players. However, this mode does not significantly impact player performance or immersion [Frommel et al. 2017]. Kao et al. [Kao et al. 2021] have shown that the game type is an important factor when designing tutorials.

In the current landscape of VR game tutorials, research has predominantly centered on these tutorials' usage scenarios and presentation formats. However, there is a notable gap in understanding the intrinsic properties of tutorials and their impact on the interaction process. This work aims to bridge this gap by dissecting the interaction process and the intrinsic attributes of VR game tutorials, offering a novel perspective on how to enhance players' gaming experience and learning efficacy. This research is of importance as it addresses a critical aspect of VR game design that has been largely overlooked: the temporal dynamics of tutorial interactions. By focusing on time flow within different tutorial windows, we aim to provide insights into how these temporal elements can be manipulated to improve player engagement and learning outcomes. Our study is unique in its approach, as it investigates the effects of bullet time and slow motion mechanics on control learnability, player performance, and engagement-related outcomes in VR game tutorials.

The contribution of this work lies in the comprehensive comparison of four tutorial modes using two VR games as experimental platforms, providing a more extensive reference for designing VR game tutorials. Our results show that bullet time, a modality that significantly reduces the players' cognitive load, improves their competitiveness, and reduces their effort, has significant benefits in terms of content learnability and suggests that the temporal factor should also be an important consideration when designing game tutorials.

2 RELATED WORK

This work draws on the cognitive theory of multimedia learning because it broadly describes the most effective principles for designing multimedia content to improve learning. Bullet time and slow motion presentation mechanisms, which manipulate users' perception of time, are chosen because they have long been recognized as ways to enhance game presentation, improving the aesthetics of games and gameplay. We also discuss game tutorials in general and work related to VR game tutorials.

2.1 Multimedia Learning

The cognitive theory of multimedia learning [Mayer 2005] encompasses three core cognitive principles: the dual channels principle, the limited capacity principle, and the active processing principle. We draw upon these core principles, which effectively and broadly delineate how to design multimedia content for learners. The dual channels principle posits that the human cognitive system comprises two independent and parallel channels, one for processing visual information and the other for auditory information. The limited capacity principle suggests that each of these independent channels in the cognitive system has a finite processing capacity at any given time. The active processing principle, also known as cognitive load, asserts that human learning is an integrative process that requires operations such as filtering, selecting, organizing, and integrating information. This information is based on the learner's prior knowledge, indicating that learning takes place within the learner's existing environment and that learners have a limited capacity for processing new information. We next explore cognitive load, which is very helpful as we explore how tutorials can be more effective in helping users learn.

2.1.1 Cognitive Load. Cognitive load refers to the cognitive processing capacity required to solve problems or learn new knowledge [Sweller 1988]. The total cognitive load is limited by our working memory, which refers to our ability to temporarily store and process information within a certain period of time. Cognitive load can be divided into intrinsic load, extraneous load, and germane load:

(1) **Intrinsic Load** is determined by the complexity and difficulty of the problem or knowledge and is related to the individual's prior knowledge.
(2) **Extraneous Load** is determined by presenting the problem, knowledge, or teaching method and is unrelated to the individual's learning objectives.
(3) **Germane Load** is determined by the cognitive processing capacity required by the individual to construct and integrate new knowledge during the learning process and is related to the individual's learning objectives.

High cognitive load can affect an individual's learning outcomes and problem-solving abilities, so appropriate strategies needs to be adopted to optimize the allocation and management of cognitive load.

According to the theory of multimedia learning, when designing multimedia learning content, one should minimize extraneous processing, manage essential processing, and foster generative processing [Clark and Mayer 2023]. These three types of processing are the main types that affect cognitive load, and here are the specific explanations for the three types of processing:

(1) **Minimizing extraneous processing** refers to reducing cognitive processing that is irrelevant to the learning objectives. For example, the design should avoid adding irrelevant background music or images, as these elements may distract learners and thus increase extraneous cognitive load.
(2) **Managing essential processing** refers to managing cognitive processing directly related to the learning objectives. For example, the design should consider how to break down complex information into smaller, more understandable parts so that learners can process the information more effectively.
(3) **Fostering generative processing** refers to fostering cognitive processing that helps learners understand and memorize new information. For example, the design should encourage

learners to engage in active learning, such as self-explanation, questioning, and summarizing, which can help learners generate new cognitive structures and thus deepen their understanding of new information.

Based on these theories of multimedia learning and cognition, the design of the tutorials in this work is guided by the following principles.

2.1.2 Signaling Principle. Visual cues are an important way to guide learners' attention and promote information acquisition [Lin and Atkinson 2011]. In VR, designers use visual cues to indicate what elements are interactive, where to look, or where to go [Dillman et al. 2018]. This is often accomplished in VR games using arrows, larger text sizes, or highlights. In VR environments, tooltips are a form of visual cues that highlight specific controller buttons and functions. Research shows that immediate tooltips speed learning and improve retention compared to delayed tooltips [Hu et al. 2020]. By employing visual cues, cognitive resources can be conserved, as users are directed towards relevant information without needing to identify it independently.

2.2 Time and Timing in Video Games

Time perception refers to the subjective assessment of time intervals and is categorized into prospective and retrospective processes according to influential models, i.e., conscious and temporary processes in which attention is focused on time and unconscious and post hoc processes in which attention is shifted away from time [Levin and Zakay 1989]. Games may affect time perception, leading to a bias in the player's estimation of the time spent in the game, i.e., the temporal runaway effect. The mind-flow state directs most of the attentional resources to the player's ongoing activities, resulting in insufficient resources allocated to time perception; therefore, entering the mind-flow state also results in altered time perception and likely underestimation of duration [Nuyens et al. 2020]. Controlling the player's time perception is a tool that game designers can utilize to enhance the player's gaming experience.

Time is an essential framework underpinning video game mechanics [Barreteau and Abrami 2007; Nitsche 2007], which determine the speed at which events unfold in the game and determines aspects of character movement, environmental change, and resource management in video games [Thavikulwat 1996]. Players make critical decisions within specific time constraints, and this dynamic adds challenge and depth to the player experience [Bogon and Halbhuber 2023]. Although the tutorial content of a game does not always require the player to make the appropriate action within a limited time, there are still game genres, such as the genres of strong continuity like rhythm games and parkour games, that require the player to interact with the game world continuously. Such game genres require the player to constantly react and make decisions within a short period of time to a certain extent, and accordingly, in the tutorials of such game genres, the player cannot avoid making decisions in a short period of time. Therefore, in order to ensure the effectiveness of the tutorial, we need to control and intervene in the tutorial to ensure that the player has a sense of agency [Guo and Lo 2023] in the game thereby ensuring effective learning..

Two of the most widely recognized temporal controls in video games are bullet time and slow motion, which can be used to effectively balance the game's difficulty curve and provide players with enough time to make decisions. Thus, the clever integration of timing mechanisms and thoughtful consideration of time elevate video games from pure entertainment to immersive and impactful experiences [Bogon and Halbhuber 2023]. A review of bullet time and slow motion is presented next.

2.2.1 Slow Motion and Bullet Time. In digital games, **slow motion** and bullet time are prominent features that significantly influence the player's experience. Slow motion, as a visual effect, originated in film and has since found its way into various genres of video games [Vibeto 2023]. It serves multiple purposes, such as emphasizing important narrative elements, highlighting on-screen action, and accentuating the spectacular qualities of in-game events [Bordwell et al. 2008]. In the context of our study, the slow-motion condition specifically refers to a mode where the game content's time flow is slowed down, while the player's physical movement inputs are decoupled from the tracking speed of the VR controller. This means that the actual hand movements of the player and the movement speed of the controller remain constant despite the game content being played in slow motion, allowing the player to better understand and learn the game operations without time pressure. The widespread use of slow motion in video games can be attributed to the evolution of game design and the increasing sophistication of game technologies that enable the implementation of such effects[Cubitt 2005].

Bullet time, a specific type of slow motion, is an interactive game mechanic that allows players to control the flow of time, giving them an advantage in overcoming in-game challenges [Vibeto 2023]. Movies like The Matrix [Wachowski et al. 1999] have popularized this mechanic, which has been incorporated into various game genres, such as action, shooter, and racing games [Schott et al. 2013]. Bullet time not only enhances the player's interactive experience but also provides a rich audiovisual spectacle, making it an essential aspect of modern game design [Brown and Krzywinska 2009].

Furthermore, the use of bullet time in video games has been linked to the concept of "juiciness," which refers to the constant stream of feedback and rewards provided to players during gameplay [Juul 2010]. Bullet time enhances the player's sensory experience by offering immediate and substantial feedback on their actions, making the game feel more vivid, interesting, and meaningful [Vibeto 2023].

In short, slow motion and bullet time have become integral components of modern video games, shaping the player's interactive experience and contributing to the game's aesthetic appeal. The existing literature highlights the importance of understanding the relationship between gameplay mechanics, audiovisual elements, and player experience in the context of slow motion and bullet time. Bullet time and slow motion can both help players understand game mechanics and enhance the game experience. However, we found little research that has applied bullet time and slow motion mechanics to game tutorials. As such, we wanted to explore what effects these two game mechanics could have when applied to tutorials in VR games.

2.3 Tutorial in Game and VR Games

The effectiveness of game tutorials varies across different contexts [Andersen et al. 2012; Frommel et al. 2017]. For complex games, tutorials can help players grasp game mechanics more quickly, enhancing their gaming experience. However, tutorials may not be necessary for simple games, as players can discover game mechanics through trial and error [Andersen et al. 2012]. In VR games, tutorial design holds equal importance. For instance, Chen et al. successfully taught players how and when to bow in a VR game designed to introduce the Japanese language and culture. The game character guided players through the bowing process, increasing their engagement with the Japanese culture. Furthermore, [Dillman et al. 2018] analyzed 49 VR games and proposed an interaction cue framework consisting of three dimensions: purpose, salience, and trigger. They discovered that certain interaction cue designs could improve players' learning outcomes and gaming experience.

The placement of notifications and prompts in VR game tutorials also significantly impacts user experience. Rzayev et al. [Rzayev et al. 2019] investigated the effects of notification placement in

VR and found that fixed notifications on the headset or walls were less likely to be overlooked than those attached to controllers or floating in the game world. This suggests that notification placement is crucial in usability and user experience. Additionally, [Wauck and Fu 2017] compared adaptive, automatic, and on-demand hint systems in a puzzle game, considering both game performance and player experience. They found that, in some cases, players (particularly beginners) were more likely to attribute their success to hints, regardless of whether these hints were genuinely helpful.

[Frommel et al. 2017] explored the impact of **context-sensitive** tutorials on player experience. They discovered that, compared to traditional instruction screen tutorials, context-sensitive tutorials in VR games elicited more positive emotions, fewer negative emotions, and higher motivation, while immersion and performance remained unaffected. Kao et al. [Kao et al. 2021] show that game type is an important factor to consider when designing tutorial patterns. For games with higher control complexity, tutorial modes are an important design aspect whose impact can extend to performance and engagement-related outcomes. Therefore, for complex VR games, developers should consider using more advanced tutorial patterns, such as controller cues.

This work is a first step in exploring tutorial presentation modes in VR, and the results may also be applicable to a wider range of VR training environments. The findings from this work highlight the significance of VR game tutorials in improving players' learning and gaming experiences.

3 WINDOWS PERIODS IN VR GAME TUTORIAL

When designing VR game tutorials, we first need to understand the interaction process between the player and the game system. This process is the core of the VR game tutorial experience, and it is different from the traditional human-computer interaction process because it involves the player's actions in the virtual environment and the game system's response. To explore this process in depth, we decompose the interaction process into several key stages and define different interaction window periods based on them.

First, the tutorial begins with an "*introduction and goal setting*" phase. In this phase, the game introduces the player to the content to be learned through various mediums (e.g., text, audio, images, etc.) and sets the related objectives. This is the starting point for the player to interact with the tutorial. Next, we move on to the "*tutorial content and level information*" phase. In this phase, the player receives the tutorial content and level information and begins to interact with the game environment through touch controls, gestures, or controller manipulation, depending on the characteristics of the VR device and game design. This is followed by the "*player input and system feedback*" phase. The system evaluates the player's interactive behavior and then provides feedback based on the player's performance. This feedback may be in-game hints, rewards, sound effects, or direct changes in the game's progress, intended to guide the player to understand better and master the game. Finally, we reach the "*mission completion and progress*" stage, where the system evaluates whether the player has successfully completed a particular tutorial objective or level requirement. If the player successfully completes the task, the game may move to the next stage or present a new challenge; if the player fails to achieve the goal, the system may provide additional guidance or feedback to help the player continue learning. Figure 1 shows the interaction process of the game tutorial.

In the traditional human-computer interaction framework, the interaction process forms a continuous loop of user input, system processing, system output, and user feedback until the user completes the task. However, in VR game tutorials, this cycle does not restart after completing the last step but ends when the player reaches the final step, after which the system opens the rest of the game by default that the player has fully mastered the corresponding learning content. To better understand the player's learning process in the tutorial, we categorize the different steps in the interaction flow into (1) **a user window period** during which the user operates and (2) **a**

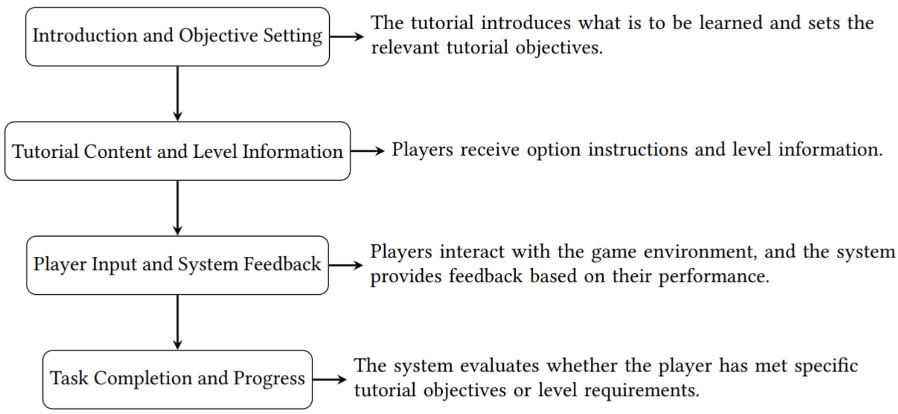

Fig. 1. Interaction process in VR Game Tutorials

system window period during which the system responds. The user window period is the phase in which the player responds to the content provided by the system, while the system window period is the phase in which the system provides the learning content and generates the exercise objectives.

In VR games, common tutorial modes include **traditional instruction screen** mode and **context-sensitive mode**. In the traditional command screen mode, the system pauses other activities while providing the instructional content and waits for the player's input while the player operates in a normal time flow. In the context-sensitive mode, both the system and the player's actions run at a normal time flow, allowing the player to receive and react to system information instantaneously. To explore the effect of different time flow rates on the player's learning outcomes, we combine the window periods of different time flow rates and define the following four tutorial modes:

- **Traditional Instruction Screen Mode**. The player needs to read the relevant text instructions before starting the tutorial content and then click on the continue button to enter the subsequent training session. During this phase, the time flow in the system window period is stopped, and the time flow in the user window period is normal.
- **Slow Motion Mode**. Slow Motion Mode enhances player learning by slowing down the time flow of game content. In this mode, the game environment and the challenges faced by the player proceed at a slower-than-normal pace, while the player's actions are maintained at normal speed. This difference in time flow creates a unique learning environment where the player can observe and practice game operations without a sense of urgency. The key to realizing this model is the decoupling of user input from the tracking speed of the VR controller. This means that the player's physical hand movements and controller movement speed remain constant despite the game content being played in slow motion. This technique allows the player to perform and learn game actions more accurately without time pressure, thus improving control learnability and overall player performance.
- **Bullet Time Mode**. The player enters the training process, and when the appropriate action needs to be performed, the time flow of the game content slows down while the player acts at normal game speed. After the player performs the action correctly, the game speed returns to normal until the following training content appears. In this mode, the time flow during the system window period is slow, while the time flow during the user window period is normal.

- **Context Sensitive Mode**. the player enters the training process, and when an appropriate action needs to be performed, the game content and the player run at normal game speed, and the player needs to make the correct action until the following training content appears. In this mode, the time flow rate for both the system window period and the user window period is at normal speed.

Table 1 (next page) shows the complete permutations of interaction window periods and time flow rates, the four modes selected are very common teaching modes and game mechanics in most video games.

Table 1. Combinations of Different Window Periods

System Window Periods	Player Window Periods	Is Reasonable (Yes/No)	Explanation
Stop	Stop	N	In this mode, the player is unable to perform any actions while the system stops waiting for input from the player. This mode can lead to confusion for the player as they are not sure when they can start an action.
Stop	Slow	N	The player's movements slow down, but the system stops responding, which may drain the player's patience. If the player's movements slow down and the system is in a state where it is waiting for input from the player, this may affect the player's gaming experience.
Stop	Normal	Y	This mode is similar to the **traditional instruction screen mode**, where the player is required to read the relevant text instructions before starting the tutorial content and clicking the continue button before moving on to the subsequent training session.
Slow	Stop	N	The system is still generating enemies and progressing through the level, albeit slowly, but the player can't make a move in the meantime, which can cause the player to become anxious.
Slow	Slow	Y	This mode can be interpreted as a **slow motion mode**. Both the player and the game content go into a slow-running state, which may help the player better understand the game action but may also require the player to adapt to this slowed-down pace.
Slow	Normal	Y	This mode can be interpreted as a **bullet time mode**, where the player moves at normal speed, but the game content runs at a slow state. This provides more time for the player to understand and adapt to the controls while keeping the game smooth.
Normal	Stop	N	The player is unable to perform any actions, yet the system is running at a normal speed, which can lead to confusion and tension for the player.
Normal	Slow	N	In this mode, the player's movements slow down while the system runs at normal speed. This can wear on the player's patience, especially if the enemy's speed stays normal while the player's slows down, giving the player negative feedback.
Normal	Normal	Y	This is the **context-sensitive tutorial mode**, where the player enters the training process and encounters moments where they need to perform the proper moves, with the game content and the player running at normal game speed. The player needs to perform the correct action before the next training content arrives.

4 EXPERIMENTAL TESTBED

We selected VR games with dynamic gameplay and continuous player actions for testing. Slower-paced games like puzzles might not need in-game tutorials, relying instead on traditional on-screen prompts or context-based guidance. Our focus is on exploring tutorial speed in different game contexts. Tutorials are suitable for games with complex mechanics, so we chose rhythm games and parkour games, two game genres that not only have complex maneuvers, but also have an extremely high level of continuity that requires the player to perform quick reactions. This study will also focus on these types of games with complex maneuvers and requiring quick reactions from the player. Drawing from previous VR tutorial research, we standardized tutorial formats using spatial orientation and text, highlighting relevant handle buttons. Both games were chosen for their adaptability, playable with arm movements in seated or standing positions, ensuring ample play space and consistent player experiences. Ahead of the study, we implemented four tutorials for each game, as outlined below.

- *Traditional instruction screen :* Players need to read the relevant text instructions before starting the tutorial content, and clicking the continue button will allow them to proceed to subsequent training sessions.
- Slow Motion Mode : When the player enters the training process and encounters a moment that requires the player to make a corresponding operation, the player and the game content will enter the slow motion mode, and when the player correctly makes the corresponding operation, the game speed will return to normal until the next set of training content arrives. In slow motion mode, the player's physical movement inputs are designed to be decoupled from the tracking speed of the VR controller. This means that the actual hand movements of the player and the movement speed of the controller remain constant despite the game content being played in slow motion, thus allowing the player to better understand and learn the game operations without time pressure.
- *Bullet time :* The player enters the training process when encountering the need for the player to make the corresponding operation of the timing, the game content will enter the slow motion mode, and the player is in the normal speed of the game when the player correctly makes the corresponding operation, the game speed to return to normal until the next set of training content arrives.
- *Context-Sensitive Mode :* When the player enters the training process and encounters a moment that requires the player to make the appropriate action, the game content and the player are at normal game speed, and the player is required to make the correct action until the next set of training content arrives.

4.1 Rhythm Game

We have developed a rhythm game inspired by the rhythmic gameplay of the game "Synth Riders" available on the Oculus platform. Our game's gameplay involves players using two different-colored balls in both hands to touch incoming balls. Players need to match balls of the same color to score points while following specific rules for consecutive touch actions and maneuvering to avoid obstacles. A schematic representation of the game is illustrated in Fig.2 a).

- The player has to make the balls on the controllers match the balls in the correct color that runs to the player.
- The player presses the trigger buttons continuously to make the balls on the controllers change color.
- The rails need the player to catch it continuously.
- Points are deducted if the player touches a BOOM.

4.2 Parkour Game

As the second experimental game, we intend to incorporate a more challenging genre focusing on the high-intensity continuous running style. Our target is akin to the continuous running gameplay seen in the "Subway Surfers" game. Players are required to perform continuous actions to evade obstacles. Fig. 2 b) provides a schematic representation of the game.

- The player has to try their best to run as far as possible and gain as high a score during gameplay. For every second the player survives, 1 point is added, and the total duration of the formal level is 90 seconds.
- The player makes parkour moves by pressing the appropriate buttons.
- Ground obstacles need to be avoided by moving left and right and jumping, and road sign obstacles need to be passed by hooking the lock.
- The player can earn extra points by shooting at targets on both sides of the road. Targets are spawned every 5 seconds, and 5 points are awarded for each target destroyed.

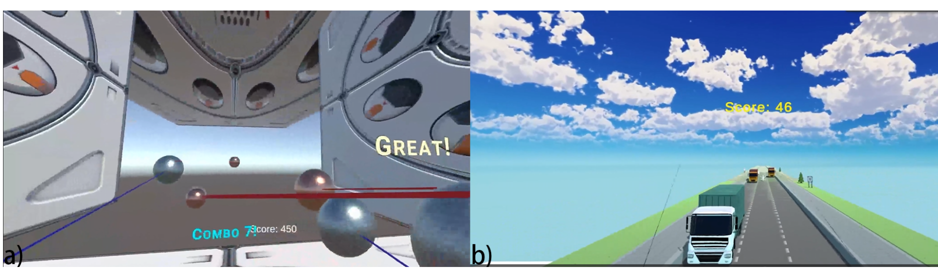

Fig. 2. Figure a) shows the gameplay of the rhythm game. Figure b) shows the gameplay of the parkour game.

5 RESEARCH METHODOLOGY

5.1 Research Questions and Hypotheses

In this project, we are primarily interested in the effects of different speeds during different windows of the game tutorial on (1) control learnability, (2) engagement-related outcomes (player experience and intrinsic motivation), and (3) player performance. Control learnability measures how easy the maneuver is to learn and generally refers to how much effort players expend to learn the corresponding maneuver. Our research question is: How does the speed of different operation windows in a game tutorial affect the players? Based on the research question, we formulate the following hypotheses:

- H1.1: Bullet time improves tutorial control learnability, player performance, and engagement-related outcomes more than traditional screen mode.
- H1.2: Bullet time improves tutorial control learnability, player performance, and engagement-related outcomes more than context-sensitive mode.
- H2.1: Slow motion improves tutorial control learnability, player performance, and engagement-related outcomes more than traditional screen mode.
- H2.2: Slow motion improves tutorial control learnability, player performance, and engagement-related outcomes more than context-sensitive mode.
- H3:Bullet time improves tutorial control learnability, player performance, and engagement-related outcomes more than slow motion mode.

H1.1 and H1.2: Bullet time mode enhances control understanding by slowing game responses while keeping player actions at normal speed, offering more time to assimilate tutorial information compared to traditional or context-sensitive modes.

H2.1 and H2.2: Slow motion mode improves control mastery by reducing overall time flow, providing extra learning time, but requires players to adapt to the slower pace.

H3: Bullet time could be more effective than slow motion since it only slows the game, not player actions, potentially boosting learning and performance without the need for pace adjustment.

5.2 Experiment Conditions

The experiment featured four tutorial types: traditional, slow motion, bullet time, and context-sensitive. Tutorials followed a consistent sequence where players first learned an action, then practiced it amidst virtual game objects like rhythm notes or parkour obstacles. Proper execution of the action allowed progression to the next tutorial part. Time flow adjustments were exclusive to the execution of correct actions under different conditions, with all other tutorial elements held constant.

5.3 Measures

Broadly, we focus on determining the impact of the speed of different option window periods in the game tutorial on control learnability (how easy the controls are found to learn), player performance (how well the participants perform after going through the game tutorial) and engagement-related outcomes (after experiencing the game tutorial, how engaged the participants are with the game). I will elaborate on the evaluation content and assessment methodology for the relevant measures.

5.3.1 Controls Learnability. To assess the learnability controls, we use the control subscale from the Player Experience of Need Satisfaction (PENS) scale [Ryan et al. 2006], which has three questions assessing controls learnability:"Learning the game controls was easy," "The game controls were intuitive," and "When I wanted to do something in the game, it was easy to remember the corresponding control." These questions were on a 7-point Likert scale (1: Do Not Agree to 7: Strongly Agree).

In addition, our measure of cognitive load utilized the NASA-TLX scale [Hart 2006], which consists of five parts on a percentage scale (1: Low to 100: High).

5.3.2 Player Performance. Player performance evaluation relies on the highest achieved scores in the games, representing participants' proficiency post-tutorial. Metrics include peak scores in rhythm games and performance in parkour games. Rhythm game scoring remains consistent for all participants due to fixed musical compositions, ensuring an equal potential for maximum scores regardless of random elements. However, in parkour games, randomness in obstacle generation and character speed progression introduces variability. Adjustments were made to standardize this randomness while maintaining its core aspect. The game controls this randomness by generating a fixed number and type of obstacles over a fixed period of time, while retaining randomized positions to ensure the player's gaming experience. A fixed play duration was enforced, ensuring consistent character movement and a standardized distance covered. Initially, game success required one minute of continuous play, but swift obstacles led to early game endings, impacting performance evaluation. Modifications were made, implementing penalties for collisions to enable smoother gameplay. Player scores were used for more accurate performance quantification in the parkour game.

5.3.3 Engagement-related Outcomes. To validate the engagement-related outcomes, we utilized subscales from the PENS questionnaire, encompassing abilities, relevance, autonomy, and immersion.

The PENS questionnaire is rooted in Self-Determination Theory. All subscales were measured using a 7-point Likert scale (1: strongly disagree, 7: strongly agree). As a supplementary assessment tool for the associated outcomes, we used the Intrinsic Motivation Inventory (IMI), which employs four dimensions to assess intrinsic motivation in activities: 1) Interest/Enjoyment (e.g., I really enjoy doing this activity), 2) Effort/Importance (e.g., I put a lot of effort into this), 3) Pressure/Tension (e.g., I feel very tense while doing this activity), and 4) Value/Usefulness (e.g., I believe this activity might be valuable to me) [McAuley et al. 1989]. All items in the scales were rated on a 7-point Likert scale.

5.3.4 Pre-test Measures. Pre-test measures were used to ensure that all participants were comparable across conditions. Two pretest measures were used in the project. One was the Simulator Sickness Questionnaire (SSQ) to assess initial simulator sickness [Kennedy et al. 1993]. The questionnaire was rated on a 4-point Likert scale (0: none to 3: severe). The other pretest measure is the Immersion Tendency Questionnaire (ITQ) to assess the participant's tendency to be immersed (e.g., write a question in this block) [Witmer and Singer 1998]. ITQ is rated on a 7-point Likert scale (1: never to 7: often). Following the two questionnaires, we asked questions related to experience with VR devices and gaming experience, such as "I have had a lot of previous experience playing video games," "I have had a lot of previous experience using VR devices," and "I have had a lot of previous experience playing VR video games," which were also rated on a 7-point Likert scale (1: strongly disagree to 7: strongly agree).

5.4 Pre-validation

To ensure the plausibility of our study, we conducted a pre-validation experiment before the formal experiment, which was primarily aimed at verifying that the effectiveness of the same tutorials receives the influence of the games' complexity. We set up a context-sensitive mode of tutorials for both games, as this tutorial mode was more popular. We then recruited eight participants to take part in the pre-experiment. Each participant would play both games and fill out the control learnability section of the PENS questionnaire for the current game at the end of each game while the game system recorded the highest score for each player. The following section presents the results of the two assessment metrics from the pre-experiment.

5.4.1 PENS Results. We use the control subscale from the PENS to assess the learnability controls. The results show that the average control learnability score for rhythm games is 6.63, and the average score for parkour games is 5. They suggest that the control learnability of rhythm games is very low, whereas the control learnability of parkour games is much higher than that of rhythm games.

5.4.2 Performance Results. We recorded the scores that players gained in the formal level to evaluate the performance of players. Rhythm games have an average score of 14,336.25 (maximum 16280, minimum 10260) in the formal level, and the score a player could get in a level would be no more than 17200. In the parkour game, the average player score in the formal level was 63.75 (maximum 138, minimum 32), well below the maximum score that could be scored in the formal level setup, 240 points. These results suggest that the parkour game was far more complex and challenging than the rhythm game.

5.5 Participants

A total of 59 participants were recruited, with each experimental group comprising 15 (Traditional Screen), 14 (Slow Motion), 15 (Bullet Time), and 15 (Context-Sensitive). All participants were recruited from university settings, with an average age of 22.55. University students generally exhibit a higher receptiveness towards VR devices and games. The table below illustrates the specifics of each experimental group.

Table 2. Participants across the four conditions.

Traditional Screen	Slow motion	Bullet time	Context sensitive
15	14	15	15

5.6 Procedure

The experimental process was divided into three phases: pre-experiment, formal experiment, and post-experiment. In the pre-experiment, participants completed the SSQ and ITQ questionnaires to assess VR adaptation and immersion. During the formal experiment, participants played two games, each with a tutorial level and an official level, using the same tutorial mode for both. After playing, they completed the PENS and IMI questionnaires to evaluate control learning, performance, motivation, and engagement.

6 ANALYSIS

After extraction and preprocessing, the data were imported into SPSS version 26 for analysis using multivariate analysis of variance (MANOVA). MANOVA was conducted to assess Controls Learnability (PENS Controls and Cognitive Load), Engagement-Related Outcomes (PENS Competence, PENS Relatedness, PENS Autonomy, PENS Immersion, IMI), Pre-Test Measures (SSQ, ITQ) – with the independent variable being tutorial condition. All dependent variables were continuous, and the independent variable of tutorial condition (Traditional Instruction Screen Mode, Slow Motion Mode, Bullet Time Mode, Context Sensitive Mode) was a four-group categorical variable. Prior to executing the MANOVA, the dataset was scrutinized for multivariate normality, homogeneity of variance-covariance matrices (via Box's M test), presence of univariate or multivariate outliers, and linearity and multicollinearity. In the event of any violation of the aforementioned assumptions, we employed the more conservative Pillai's Trace; otherwise, Wilk's Lambda was utilized. Post hoc tests were performed using the Bonferroni test. Effect sizes were quantified using partial-eta squared (.01 for small, .06 for medium, and .14 for large effects).

7 RESULTS

7.1 Summary Descriptives

At the end of the experiment, we briefly asked the participants if they had ever played a similar game before. No participant said that they had played a similar game before. All participants showed low SSQ scores. For each group, the SSQ scores are reported as follows: Traditional Screen Mode (Minimum = 0, Maximum = 11.22, Median = 3.74), Slow Motion Mode (Minimum = 0, Maximum = 18.7, Median = 0), Bullet Time Mode (Minimum = 0, Maximum = 18.7, Median = 0), Context Sensitive Mode (Minimum = 0, Maximum = 11.22, Median = 0).

ITQ scale scores for each group are reported as follows: Traditional Screen Mode (Minimum = 3.29, Maximum = 5.79, Median = 4.79), Slow Motion Mode (Minimum = 3.33, Maximum = 6.67, Median = 4.81), Bullet Time Mode (Minimum = 3.55, Maximum = 6.81, Median = 4.98), Context Sensitive Mode (Minimum = 3.17, Maximum = 6, Median = 4.43).

The following section describes the results for each experimental condition. For an overview of the results, see Figures 3, 4, and 5.

7.2 Game 1: Rhythm Game

The results related to the rhythm game are reported first.

Pre-test: No statistically significant differences were found between SSQ, ITQ, and prior gaming experience and the tutorial condition-based VR gaming experience with the test measures.

Controls Learnability: Our results show a statistically significant difference in control learnability based on tutorial conditions, F(6,78)=2.51, $p<0.05$, $\eta^2=0.162$. Univariate tests found significant differences in both PENS Control and Cognitive Load. The indicators of the PENS Control component were as follows: F=3.23, $p<0.05$, $\eta^2=0.195$. The indicators of the Cognitive Load component were as follows: F=6.518, $p<0.005$, $\eta^2=0.328$. The bullet time mode in the PENS Control section was found to be significantly higher than the context-sensitive mode in post hoc tests, $p<0.05$. For the Cognitive Load section, see the right image of Figure 5, bullet time was significantly lower than all the other three tutorial modes, traditional screen ($p<0.005$), context-sensitive ($p<0.05$), and slow motion ($p<0.05$).

Engagement-Related Outcomes: We found statistically significant differences in participation-related outcomes based on tutorial conditions, F(28,98)=2.52, $p<0.005$, $\eta^2=0.338$. Further tests found that differences in participation-related outcomes based on the tutorial condition were significant in the PENS Competence section (F=4.11, $p<0.05$, $\eta^2=0.236$), IMI Effort (F=3.32, $p<0.05$, $\eta^2=0.199$), and IMI Pressure sections (F=3.315, $p<0.05$, $\eta^2=0.225$). Post hoc tests revealed that bullet time was significantly better than traditional command screen mode in the PENS Competence section ($p<0.05$). In the IMI Effort section, the bullet time mode was significantly less effortful than the context-sensitive mode ($p<0.05$).

Player Performance: The score of player performance for each tutorial group is as follows: Traditional Screen Mode (Minimum = 10070, Maximum = 14480, Median = 12570), Slow Motion Mode (Minimum = 10130, Maximum = 16160, Median = 14690), Bullet Time Mode (Minimum = 12350, Maximum = 16420, Median = 14680), Context Sensitive Mode (Minimum = 9860, Maximum = 14910, Median = 12690), for each player, the maximum score that can be obtained in a single game is 17200. Differences in player performance based on tutorial conditions were statistically significant, F(3,40)=3.45, $p<0.05$, $\eta^2=0.206$. Post hoc tests revealed that players in bullet-time mode performed significantly better than those in context-sensitive mode, $p<0.05$.

7.3 Game 2: Parkour Game

Next, this section reports results related to parkour games.

Pre-test: No statistically significant differences were found between the SSQ, ITQ, and prior gaming experience and the tutorial condition-based VR gaming experience with the test measures.

Controls Learnability: We found a statistically significant difference in control learnability based on the tutorial condition, F(6,78)=1.68, $p<0.05$, $\eta^2=0.594$. Univariate tests found significant differences for PENS control. The indicators for the PENS Control component are as follows: F=3.40, $p<0.05$, $\eta^2=0.204$. Post hoc testing found that the bullet time mode in the PENS control section was significantly higher than the traditional instruction screen mode, $p<0.05$.

Engagement-Related Outcomes: We found a statistically significant difference in participation-related outcomes based on the tutorial condition, F(21,98)=1.66, $p<0.005$, $\eta^2=0.253$. The univariate test found that the participation-related results based on the coaching conditions were in the PENS ability part (F=2.86, $p<0.05$, η^2=0.0.325), IMI effort part (F=2.57, $p<0.05$, $\eta^2=0.195$) has a significant difference. Post hoc tests showed that the context-sensitive mode was better than the slow-motion mode in the PENS capability section ($p<0.05$). In the IMI effort component, the bullet time mode was significantly less effortful than the context-sensitive mode ($p<0.05$).

Player Performance: The score of player performance for each tutorial group is as follows: Traditional Screen Mode (Minimum = 50, Maximum = 130, Median = 85), Slow Motion Mode (Minimum = 60, Maximum = 165, Median = 130), Bullet Time Mode (Minimum = 60, Maximum = 165, Median = 125), Context Sensitive Mode (Minimum = 60, Maximum = 160, Median = 115), for each player, the maximum score that can be obtained in a single game is 240. Differences in player performance based on tutorial conditions were not statistically significant, F(3,40)=1.25, p = 0.304, η^2=0.086.

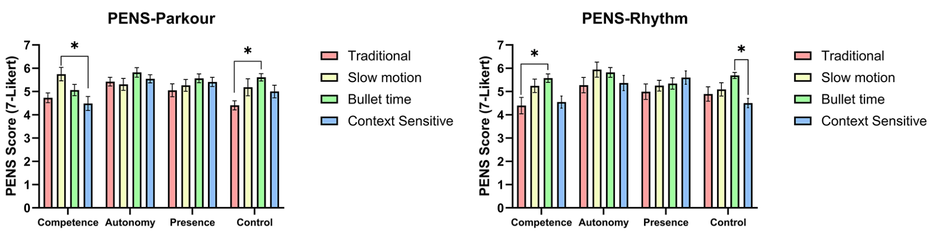

Fig. 3. Player Experience of Need Satisfaction results. Asterisk (*) indicates a significant difference between tutorial condition types. Error bars show SEM.

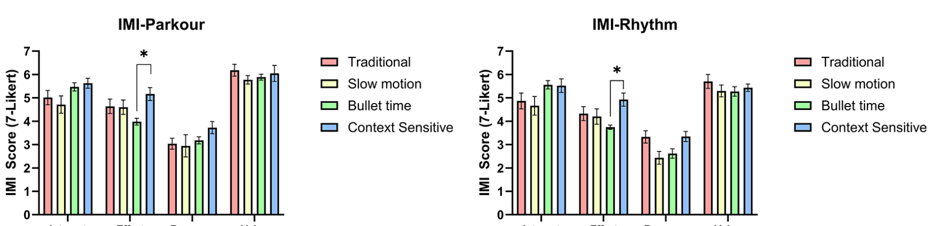

Fig. 4. Intrinsic Motivation Inventory results. Asterisk (*) indicates a significant difference between tutorial condition types. p < .05 (*). Error bars show SEM.

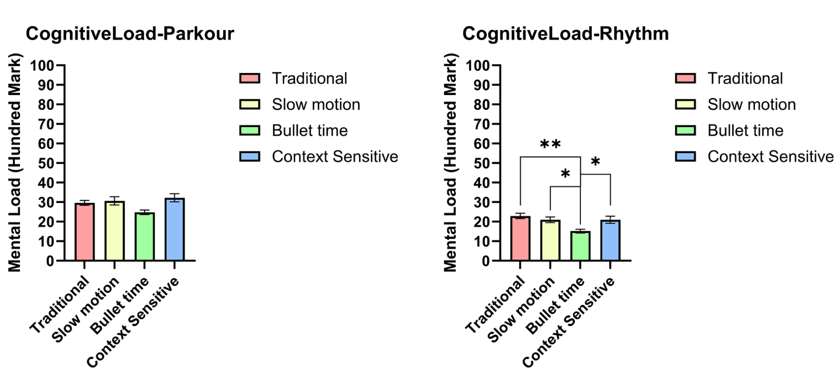

Fig. 5. Cognitive Load results. Asterisk (*) indicates a significant difference between tutorial condition types. p < .05 (*), p<0.005 (**). Error bars show SEM.

7.4 Player Feedback

After the experiment, we interviewed participants about the effectiveness of different tutorial models in teaching game controls and whether the time flow rates needed adjustment. Most from the traditional mode found it ineffective due to the need to stop and read, often forgetting previous content. Some slow-motion participants suggested a faster time flow rate, while context-sensitive mode users wanted more time to react and learn. Bullet time users generally found it helpful for learning but recommended system time flow adjustments for optimal teaching outcomes.

8 DISCUSSION

Our work provides insights into the suitability of different tutorial modes for VR games with different temporal flow rates, particularly concerning their effects on controlled learnability, player engagement, and performance. Our experimental results validate the core principles of multimedia learning theory and fit with the self-determination theory on intrinsic motivation. These findings provide valuable insights into understanding the effectiveness of tutorial design for VR games and provide practical guidance for game designers.

The bullet time mode significantly improves control learnability, which is consistent with our expected results. In this mode, the time flow of the game content slows down while the player performs actions that remain normal. This design allowed the player more time to understand and adapt to the game actions, thereby reducing cognitive load. This finding is consistent with cognitive load theory, which emphasizes the importance of efficiently managing cognitive resources within a limited working memory. By slowing down the temporal flow of game content, the bullet-time model provides players with additional cognitive space, allowing them to absorb and apply new information more efficiently. Second, the bullet-time model also showed significant effects in enhancing player engagement and motivation. This is consistent with the self-determination theory of intrinsic motivation, which posits that players' intrinsic motivation is enhanced when they feel autonomous, empowered, and relevant.

In addition, our findings suggest that the bullet time mode enhances players' sense of autonomy and competence by providing additional time to understand and master game operations, which in turn increases their engagement and motivation. This model not only reduces players' cognitive load but also enhances their controlled learning by providing more time to adapt to the game operations. In addition, our study reveals an interaction between game complexity and the effectiveness of the bullet-time model. For games with complex operations, the bullet time mode may be more effective because it provides more time for players to adapt and learn. This finding emphasizes that game designers should consider the difficulty of the game and the player's learning curve when designing tutorials. For complex VR games, bullet time mode may be an effective tool because it helps players better understand and master the game operations.

While our work provides new perspectives on VR game tutorial design, there are some limitations. Our study sample was primarily drawn from university settings, which may not fully represent the broader player population. In addition, our study only covered two types of games, which may limit the generalizability of our results. In the future, we plan to run further studies with a wider variety of games and a broader group of participants to verify the applicability of our findings across different gaming environments and player groups. Also, our work did not explore the long-term effects of the bullet time mode on player learning, such as player performance and memory retention after the tutorial. Our future plan includes further exploration of the sustained effects of bullet time patterns on player learning outcomes at different points in time. Despite these limitations, the findings contribute to understanding VR game tutorials and offer practical guidance for game designers. The potential of the bullet time mode to improve the learning curve and gaming experience is a promising direction for future research and application in VR gaming.

9 CONCLUSION

This research has provided a comprehensive examination of the impact of different window periods in VR game tutorials, with a particular focus on the innovative use of bullet time and slow motion techniques. Our findings can have significant implications for the design of VR tutorials, offering insights into how the manipulation of time flow can enhance player engagement, learning efficiency, and overall gaming experience.

The results indicate that bullet time, which allows players to interact at normal speed while the game system's response is slowed down, is particularly effective in reducing cognitive load and improving control learnability and player performance. This aligns with the principles of multimedia learning theory, which emphasizes the importance of managing cognitive load and fostering active processing. The bullet time mode provides players with the necessary cognitive space to absorb and apply new information effectively, leading to a more engaging and immersive learning experience.

The findings of this research contribute to the broader academic discussion on VR game tutorials and offer practical guidance for game designers. Integrating bullet time into VR game tutorials represents a promising direction for enhancing the learning curve and ensuring a more immersive and enjoyable gaming experience for players.

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REFERENCES

Thomas Alsop. 2021. Forecast augmented (AR) and virtual reality (VR) market size worldwide from 2020 to 2024. *Stat. com. Publ* (2021).

Erik Andersen, Eleanor O'rourke, Yun-En Liu, Rich Snider, Jeff Lowdermilk, David Truong, Seth Cooper, and Zoran Popovic. 2012. The impact of tutorials on games of varying complexity. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 59–68.

Nilufar Baghaei, Vibhav Chitale, Andrej Hlasnik, Lehan Stemmet, Hai-Ning Liang, and Richard Porter. 2021. Virtual Reality for Supporting the Treatment of Depression and Anxiety: Scoping Review. *JMIR Ment Health* 8, 9 (23 Sep 2021), e29681. https://doi.org/10.2196/29681

Olivier Barreteau and Géraldine Abrami. 2007. Variable time scales, agent-based models, and role-playing games: The PIEPLUE river basin management game. *Simulation & Gaming* 38, 3 (2007), 364–381.

Leif P. Berg and Judy M. Vance. 2017. Industry use of virtual reality in product design and manufacturing: a survey. *Virtual Reality* 21, 1 (2017), 1–17. https://doi.org/10.1007/s10055-016-0293-9

Johanna Bertram, Johannes Moskaliuk, and Ulrike Cress. 2015. Virtual training: Making reality work? *Computers in Human Behavior* 43 (2015), 284–292.

Johanna Bogon and David Halbhuber. 2023. Time and Timing in Video Games: How Video Game and Time Perception Research can benefit each other. (2023).

David Bordwell, Kristin Thompson, and Jeff Smith. 2008. *Film art: An introduction*. Vol. 8. McGraw-Hill New York.

Douglas Brown and Tanya Krzywinska. 2009. Movie-games and game-movies: Towards an aesthetics of transmediality. (2009).

Ruth C Clark and Richard E Mayer. 2023. *E-learning and the science of instruction: Proven guidelines for consumers and designers of multimedia learning*. john Wiley & sons.

Sean Cubitt. 2005. *The cinema effect*. Mit Press.

Kody R Dillman, Terrance Tin Hoi Mok, Anthony Tang, Lora Oehlberg, and Alex Mitchell. 2018. A visual interaction cue framework from video game environments for augmented reality. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–12.

Julian Frommel, Kim Fahlbusch, Julia Brich, and Michael Weber. 2017. The Effects of Context-Sensitive Tutorials in Virtual Reality Games.(2017), 367–375. *DOI: https://doi. org/10.1145/3116595.3116610* (2017).

Zixuan Guo and Cheng-Hung Lo. 2023. An Empirical Framework for Understanding a Player's Sense of Agency in Games. *International Journal of Human–Computer Interaction* (2023), 1–20.

Sandra G Hart. 2006. NASA-task load index (NASA-TLX); 20 years later. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 50. Sage publications Sage CA: Los Angeles, CA, 904–908.

Xinyu Hu, Alec Moore, James Coleman Eubanks, Afham Aiyaz, and Ryan P. McMahan. 2020. Evaluating interaction cue purpose and timing for learning and retaining virtual reality training. In *Proceedings of the 2020 ACM Symposium on Spatial User Interaction*. 1–9.

Jesper Juul. 2010. *A casual revolution: Reinventing video games and their players*. MIT press.

Dominic Kao, Alejandra J Magana, and Christos Mousas. 2021. Evaluating tutorial-based instructions for controllers in virtual reality games. *Proceedings of the ACM on Human-Computer Interaction* 5, CHI PLAY (2021), 1–28.

Robert S Kennedy, Norman E Lane, Kevin S Berbaum, and Michael G Lilienthal. 1993. Simulator sickness questionnaire: An enhanced method for quantifying simulator sickness. *The International Journal of Aviation Psychology* 3, 3 (1993), 203–220.

Glyn Lawson, Davide Salanitri, and Brian Waterfield. 2016. Future directions for the development of virtual reality within an automotive manufacturer. *Applied ergonomics* 53 (2016), 323–330.

Hyeopwoo Lee, Hyejin Kim, Diego Vilela Monteiro, Youngnoh Goh, Daseong Han, Hai-Ning Liang, Hyun Seung Yang, and Jinki Jung. 2019. Annotation vs. Virtual Tutor: Comparative Analysis on the Effectiveness of Visual Instructions in Immersive Virtual Reality. In *2019 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. 318–327. https://doi.org/10.1109/ISMAR.2019.00030

Iris Levin and Dan Zakay. 1989. *Time and human cognition: A life-span perspective*. Elsevier.

Ziming Li, Airong Wang, Diego Monteiro, and Hai-Ning Liang. 2023. Virtual reality in academic English writing: exploring factors influencing abstract knowledge learning. *Virtual Reality* 27 (2023), 2927–2939. https://doi.org/10.1007/s10055-023-00847-3

Lijia Lin and Robert K Atkinson. 2011. Using animations and visual cueing to support learning of scientific concepts and processes. *Computers & Education* 56, 3 (2011), 650–658.

Feiyu Lu, Difeng Yu, Hai-Ning Liang, Wenjun Chen, Konstantinos Papangelis, and Nazlena Mohamad Ali. 2018. Evaluating Engagement Level and Analytical Support of Interactive Visualizations in Virtual Reality Environments. In *2018 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. 143–152. https://doi.org/10.1109/ISMAR.2018.00050

Richard E Mayer. 2005. *The Cambridge handbook of multimedia learning*. Cambridge university press.

Edward McAuley, Terry Duncan, and Vance V Tammen. 1989. Psychometric properties of the Intrinsic Motivation Inventory in a competitive sport setting: A confirmatory factor analysis. *Research quarterly for exercise and sport* 60, 1 (1989), 48–58.

Diego Monteiro, Teng Ma, Yue Li, Zhigeng Pan, and Hai-Ning Liang. 2022. Cross-cultural factors influencing the adoption of virtual reality for practical learning. *Universal Access in the Information Society* (2022). https://doi.org/10.1007/s10209-022-00947-y

Diego Monteiro, Airong Wang, Luhan Wang, Hongji Li, Alex Barrett, Austin Pack, and Hai-Ning Liang. 2024. Effects of Audience Familiarity on Anxiety in a Virtual Reality Public Speaking Training Tool. *Universal Access in the Information Society* 23 (2024), 23–34. https://doi.org/10.1007/s10209-023-00985-0

Michael Nitsche. 2007. Mapping Time in Video Games.. In *DiGRA Conference*.

Filip M Nuyens, Daria J Kuss, Olatz Lopez-Fernandez, and Mark D Griffiths. 2020. The potential interaction between time perception and gaming: A narrative review. *International Journal of Mental Health and Addiction* 18 (2020), 1226–1246.

Tyler Rose, Chang S Nam, and Karen B Chen. 2018. Immersion of virtual reality for rehabilitation-Review. *Applied ergonomics* 69 (2018), 153–161.

Richard M Ryan, C Scott Rigby, and Andrew Przybylski. 2006. The motivational pull of video games: A self-determination theory approach. *Motivation and emotion* 30 (2006), 344–360.

Rufat Rzayev, Sven Mayer, Christian Krauter, and Niels Henze. 2019. Notification in vr: The effect of notification placement, task and environment. In *Proceedings of the annual symposium on computer-human interaction in play*. 199–211.

Gareth Schott, Raphaël Marczak, Frans Mäyrä, and Jasper van Vught. 2013. DeFragging Regulation: From putative effects to'researched'accounts of player experience.. In *DiGRA Conference*.

John Sweller. 1988. Cognitive load during problem solving: Effects on learning. *Cognitive science* 12, 2 (1988), 257–285.

Chek Tien Tan, Tuck Wah Leong, Songjia Shen, Christopher Dubravs, and Chen Si. 2015. Exploring gameplay experiences on the oculus rift. In *Proceedings of the 2015 annual symposium on computer-human interaction in play*. 253–263.

Precha Thavikulwat. 1996. Activity-driven time in computerized gaming simulations. *Simulation & Gaming* 27, 1 (1996), 110–122.

Håvard Andreas Vibeto. 2023. Slow Motion in Videogames—Gameplay Over Style? *Games and Culture* 18, 3 (2023), 283–299.

Andy Wachowski, Larry Wachowski, Keanu Reeves, Laurence Fishburne, Carrie-Anne Moss, Hugo Weaving, Gloria Foster, Joe Pantoliano, and Zach Staenberg. 1999. *Matrix*. Warner Home Video Burbank, CA.

Jialin Wang, Rongkai Shi, Zehui Xiao, Xueying Qin, and Hai-Ning Liang. 2022. Effect of Render Resolution on Gameplay Experience, Performance, and Simulator Sickness in Virtual Reality Games. *Proc. ACM Comput. Graph. Interact. Tech.* 5, 1, Article 7 (may 2022), 15 pages. https://doi.org/10.1145/3522610

Liu Wang, Mengjie Huang, Rui Yang, Hai-Ning Liang, Ji Han, and Ying Sun. 2023. Survey of Movement Reproduction in Immersive Virtual Rehabilitation. *IEEE Transactions on Visualization and Computer Graphics* 29, 4 (2023), 2184–2202. https://doi.org/10.1109/TVCG.2022.3142198

Helen Wauck and Wai-Tat Fu. 2017. A data-driven, multidimensional approach to hint design in video games. In *Proceedings of the 22nd international conference on intelligent user interfaces*. 137–147.

Bob G Witmer and Michael J Singer. 1998. Measuring presence in virtual environments: A presence questionnaire. *Presence* 7, 3 (1998), 225–240.

Wenge Xu, Hai-Ning Liang, Nilufar Baghaei, Xiaoyue Ma, Kangyou Yu, Xuanru Meng, and Shaoyue Wen. 2021a. Effects of an Immersive Virtual Reality Exergame on University Students' Anxiety, Depression, and Perceived Stress: Pilot Feasibility and Usability Study. *JMIR Serious Games* 9, 4 (22 Nov 2021), e29330. https://doi.org/10.2196/29330

Wenge Xu, Hai-Ning Liang, Kangyou Yu, and Nilufar Baghaei. 2021b. Effect of Gameplay Uncertainty, Display Type, and Age on Virtual Reality Exergames. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (<conf-loc>, <city>Yokohama</city>, <country>Japan</country>, </conf-loc>) *(CHI '21)*. Article 439, 14 pages. https://doi.org/10.1145/3411764.3445801

Wenge Xu, Hai-Ning Liang, Kangyou Yu, Shaoyue Wen, Nilufar Baghaei, and Huawei Tu. 2023. Acceptance of Virtual Reality Exergames Among Chinese Older Adults. *International Journal of Human–Computer Interaction* 39, 5 (2023), 1134–1148. https://doi.org/10.1080/10447318.2022.2098559

Kangyou Yu, Shaoyue Wen, Wenge Xu, Maurizio Caon, Nilufar Baghaei, and Hai-Ning Liang. 2023. Cheer for me: effect of non-player character audience feedback on older adult users of virtual reality exergames. *Virtual Reality* 27 (2023), 1887–1903. https://doi.org/10.1007/s10055-023-00780-5