Play with my Expectations: Players Implicitly Anticipate Game Events Based on In-Game Time-Event Correlations

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ABSTRACT

Temporal regularities and the timing of events and actions such as anticipating enemy movements or planning one's next move are essential components of almost every video game. Thus, to succeed in video games, it is advantageous to anticipate events and prepare relevant actions before they occur. This work explores whether elapsed time can be used as a predictive cue for implicitly anticipating events in video games. Inspired by findings from psychology, we implemented multiple time-event correlations in a custom video game by pairing specific delays with specific game events. Participants had to shoot targets that appeared at different locations. After a certain delay (e.g., 0.8 s), the targets appeared more frequently (80 % of all appearances) at a specific location (e.g., left up). Our analysis of 25 participants provides evidence that players implicitly learned the implemented time-event correlations and used them to anticipate the location of upcoming targets. This led to improved game performance. Although no participant realised the implemented temporal regularities, targets were shot faster when preceded by the frequently paired delay. Our findings pave the way for game developers and researchers alike to more creatively combine human temporal processing with temporal aspects of video games.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; **Interaction techniques**.

KEYWORDS

video games, time and timing in video games, time perception in video games, time-based event expectancy

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1 INTRODUCTION

Temporal regularities and the timing of events and actions are essential elements of almost every video game. Regardless of whether a player waits for a skill to be ready in *Apex Legends* [14], anticipates when and where an enemy is going to attack in *Counter-Strike 2* [61] or estimates the perfect moment to utilize *Returnal*'s *Overload* [63] mechanic, which, if timed correctly, drastically increases weapon reloading speed in the shooting game, timing is crucial.

In our daily lives, we constantly use time to anticipate events. Consider, for example, how one's expectancy changes while ringing a doorbell and waiting for a response. As time passes, we first expect the door to be opened and prepare to greet the residents. After a certain waiting time, this expectancy changes to anticipating an unanswered doorbell, and we prepare to leave. In cognitive psychological research, this anticipatory behavior based on temporal information is called time-based event expectancy [58] and has been studied applying the time-event correlation paradigm [55, 58, 65]. In this paradigm, mostly two events are coupled to different foreperiods, which is the time passed before the event happens. The probabilities of the events are identical, but crucially the combination of event and corresponding foreperiod is not. One combination is more frequent, while the other is less frequent. Frequent combinations are also referred to as valid since they allow, through their prevalence, the formation of a temporal mental representation of the event. Conversely, infrequent combinations are the exception and are thus also called invalid. Using this paradigm, studies showed that after a certain learning period, participants respond faster to events that are part of a valid time-event combination than to events that are part of an invalid time-event combination [55, 57]. However, currently it is unclear if video game players can profit from the same systematic performance increase.

To answer this question, we explore a new concept of using temporal structures of video games, so-called time-event correlations, to influence player behavior and performance. We investigate whether players learn multiple associations between specific delays and game events and improve their performance by implicitly using these learned associations to anticipate game events and their required actions. To achieve this, we developed a 3D shooting game and coupled time-event correlations to the in-game targets' mechanics. However, contrary to classical time-event correlation studies from cognitive psychological research that use mostly two time-event correlations, we implemented four different time-target combinations. We did this to appropriately reflect the larger interaction space (compared to classical psychological experiments) of nowadays' video games, such as character movement, visual and auditory feedback, and in-game scores. In our game, players must shoot targets spawning at four lateral locations with four different foreperiods. After a certain foreperiod (e.g., 0.8 s), the targets appeared more frequently (80 % of all appearances) at a specific location (e.g., left up). We used the game to conduct a study with 28 players. Our study investigates the *implicit* adaptation to time-target combination. Hence, we excluded three participants from the data analysis whose answers to the post-experience interview indicates that they *explicitly* noticed the temporal regularities in the game. Analysis of the data from 25 players who did not notice the regularities provides evidence that players implicitly learned the implemented time-target combinations and used them to anticipate the location of upcoming targets, which led to improved game performance. Although none of the analyzed participants explicitly realised the implemented temporal regularities, on average targets were shot 32 ms faster when the frequently paired foreperiod preceded them, while the error rate remained constant. Hence, our work provides first evidence that players in video games can implicitly utilize multiple time-target combinations to form a solid mental representation of the temporal regularities of a game. Game developers can benefit from our findings by implementing time-event correlations to adjust game difficulty, balance uncertainty and predictability or augment unavoidable delays with information. We provide all material via *Open Sciences Framework* (OSF) to enable future research to build on our work. The repository includes the game's source codes, all the gathered anonymized user data, as well as the full statistical analysis[1].

2 RELATED WORK

A large body of work investigates time and time perception in video games from different angles: Researching time as a game element, through the eye of latency, or how video games alter the subjective time perception of players. Furthermore, research on temporal cognition provides a phenomenon that could elucidate anticipatory player behavior in video games: Time-based event expectancy.

In the following, we first discuss how time influences video game design and mechanics and show that research on latency demonstrates that players are sensible to temporal disturbances. Next, we discuss how playing video games alters the players' time perceptions. We provide an overview of how time-based event expectancy influences behavior and elucidate how it is investigated in cognitive psychology. We conclude this section by summarizing why temporality must be considered when designing games and game mechanics.

2.1 Time in Video Games

Time is a crucial concept underpinning video game mechanics [3, 39]. It dictates the pace at which events unfold and determines character movements, environmental changes, and resource management in video games [53]. Players make decisions within specific time constraints, a dynamic that adds challenge and depth to the players' experiences. From the urgency of a time-sensitive puzzle to the patience required for strategic planning, manipulating time within gameplay mechanics offers designers numerous ways to incorporate opportunities and consequences.

Researchers study time in video games from a number of different perspectives, for example: (1) time as a game mechanic, (2) time as a measure of latency, or (3) time as a key element of predictability in video games. Research on time, in general, elucidates how players in video games are situated in game-specific time frames [39], how to integrate multiple time scales in a single game [3] or how activities are paced and synchronized in video games [53]. Other work in this line investigates how much time players spend on video games [59], how adolescents underestimate time spent on gaming [60], or how video games enhance temporal processing abilities [13]. While all of this work, directly or indirectly, states that time is a crucially important concept in video games, none focuses on temporal cognition.

The second perspective on time in video games is by understanding the effects of latency. Latency is the time between an user's input and a system's output [67] and, fundamentally, every interactive system is affected by it [35]. When investigating temporal components of video games, it is crucial to account for latency and its effects, since previous work showed that even small variations in temporal changes can affect experience and performance. Previous work, for example, demonstrated that latency above 25 ms leads to a decreased user performance [1, 29] when using touch-based systems. In later work, Ng et al. [38] even found that users can perceive latency starting at a value of 2 ms. The authors show in subsequent work that users even could distinguish between 1 ms and 2 ms of latency [37]. Since video games are interactive systems as well, they are also affected by latency [10, 20]. Latency decreases player performance [19, 21, 49] and gaming experience [6, 15, 24]. Other work, for example, by Halbhuber et al. [23], demonstrated that the mere expectation of latency in video games induces an adverse placebo (nocebo) effect in video game players. To summarize, work on latency in video games demonstrates that minor temporal disturbances of the input-output paradigm and even the expectation of latency can disturb gaming performance and experience.

Another perspective on time and its effects on players in video games offers work on predictability. Temporal predictability in video games, the ability to temporally predict game events based on the current or past game states, allows players to effectively divide their attention [62] to optimize the use of in-game resources in *real-time strategy* (RTS) games such as *StarCraft 2*. Predictability

[1]https://osf.io/kjp9e

is even used as a critical element in certain games such as the *First-Person Shooter* (FPS) game *SUPERHOT* [52]. In *SUPERHOT*, time only moves if the player's avatar moves. Thus, if the avatar stands still, enemies' movement and hostile projectiles are slowed down to near-standstill. This distorted temporality allows the player to carefully plot maneuvers, plan strategies, and predict how the game will play out in the future [26].

2.2 Time Perception in Video Games

Research on time perception in video games focuses on how video games alter players' perceptions of time. For example, Rutrecht et al. [47] found that players' subjective time perception correlates with their experienced flow. Flow, firstly described in 1975 by Csikszentmihalyi [12, 27, 36], corresponds to the mental state of *being in the zone*. This state includes being highly focused and a strong feeling of immersion with a high level of enjoyment and fulfillment. In their work, Rutrecht et al. [47] showed that the higher the flow level while playing, the shorter the perceived subjective time. Nuyens et al. [40] argue that *being in the zone* requires players to direct their attentional resources to the activity at hand, which leads to fewer mental resources allocated to time perception. The authors conclude that entering a flow state mainly results in underestimating subjective time. Other research in this line of work investigates the effects of in-game music on time perception [46, 48]. For example, Rogers et al. [46] found that playing virtual reality video games with music leads to a significantly faster passing of time compared to playing without music. In similar work, Cassidy & MacDonald [9] investigated the effects of music on time perception and performance in a video game. The authors found that participants playing with self-selected music resulted in an overestimation of elapsed time. Furthermore, the authors argue that the over-estimation stems from the self-selected music being associated with personal meaning and, thus, increased engagement with the ongoing activity. While research on time in video games and time perception in video game is crucial to understand the general framework of temporality in games, it does not answer how and if players can utilize temporal regularities in games to increase their performance and experience.

2.3 Time-based Event Expectancy

Time-based event expectancy describes the ability to anticipate an event based on the time that has elapsed until the event occurs. Rather than just asking "*when?*" it corresponds to "*what based on when?*" [2]. Initially introduced in a cognitive psychological study by Wagener and Hoffmann [65], time-based event expectancy is investigated using the time-event correlation paradigm [55, 58, 65]. Two distinguishable events (event A and event B) occur after two different foreperiods (foreperiod A and foreperiod B). Both events are equally probable; however, the time-event correlation is not. In the majority of all trials, foreperiod A leads to event A and foreperiod B leads to event B (valid combinations). Crucially, in a minority of all trials of all tested cases, foreperiod A leads to event B, and foreperiod B leads to event A (invalid combinations). To allow observers to unintentionally and subconsciously learn relationships between duration and events [64], researchers apply clearly distinguishable values for both foreperiods, such as 600 ms (foreperiod A) and 1.400 ms (foreperiod B) [65]. Other work investigating time-based event expectancy used 400 ms and 1000 ms [55] or 500 ms and up to 1500 ms [58] to induce time-based event correlations. Research in this line of work showed that response times to an event in a valid time-event combination are significantly lower relative to those in invalid combinations [56, 58], even though participants are not aware of the temporal regularities of the task at hand [64]. While most studies investigating time-based expectancy have explored the effects of two time-event correlations, only one study provides evidence that humans can adapt to multiple (three) time-event correlations [2]. This is particularly relevant in light of video games. In video games, players typically separate their focus on multiple in-game actions and elements, such as shooting different targets, keeping track of their performance, and processing multimodal feedback. Previous work does not answer if the increased attentional resources required to play video games prevent players from forming implicit time-based event expectancy.

2.4 Summary

A large body of work investigates time in video games from different perspectives, for example: Time as a game mechanic [3, 4, 39], time through the eye of latency [10, 11, 19, 24, 33], the effects of (temporal) predictability on player experience [26, 62], or how video games alter the subjective perception of time in players [46–48]. Altogether, previous work clearly shows that understanding time and timing in video games is essential for designing video games and crucial for understanding player behavior and how temporal components in video games, such as latency, alters it. Furthermore, psychological research provides a concept of temporal expectancies that elucidates anticipatory behavior: time-based event expectancy [2, 58, 65]. Previous work highlighted that humans' response times are significantly decreased when upcoming events are made predictable through time-event correlations [56]. Considering the advantages video game players could gain, it stands to reason that the integration of time-based event expectancy in video games should be investigated. Currently, however, it is unknown if the increased attentional resources required when playing video games hamper the ability to form implicit time-based event expectancy. Furthermore, it is unclear whether it is possible to adapt to multiple time-event correlations, a scenario that better reflects the large interaction space of video games. Ultimately, time-based event expectancy may be used to alter the predictability of a video game, which, in turn, may increase overall gaming experience and performance.

3 INVESTIGATING TIME-BASED EVENT EXPECTANCY IN VIDEO GAMES

We designed and implemented a custom 3D FPS game to investigate whether time-event-correlations are applicable as game elements in video games. We explore whether players can adapt to multiple time-event correlations, which potentially leads to an increase in performance. Developing a custom game ensures complete control over the research environment. Furthermore, we developed a game from the FPS genre, as they are susceptible to temporal disturbances [5, 33]. Split-second decision-making and reactions are crucial to playing FPS games effectively, contrary to, for example, a turn-based strategy game which does not necessarily create temporal pressure. After developing the game's foundation, we implemented game mechanics to potentially influence gamers' performances through time-based event expectancy. We then integrated multiple functions to log player behavior and performance, such as mouse position, reaction time, and accuracy. Employing this setting, we conducted an experiment with 28 participants. The participants were instructed to play our game for approximately 40 minutes while we recorded the aforementioned in-game data.

3.1 Game Development

We developed and designed our game in the style of the commercially available game *Aim Lab* [50]. *Aim Lab* is a so-called aim trainer and is regularly played by millions of players [32]. Aim trainers seek to improve player skills in FPS games, such as the players' accuracy or reaction times. These types of games are highly performance-oriented and omit other typical elements of games, such as a story. However, as aim trainers incorporate typical atomic FPS game mechanics, such as target tracking and selection, they are well suited as a platform to investigate time-based event expectancy in video games. Their fundamental mechanics, for example, tracking and shooting targets, allow us to generalize potential findings of our work to the broader FPS genre. We used the *Unity3D* (Version 2020.3.14f1) game engine for development. After developing basic game mechanics and the game world, we integrated detailed mechanics designed around the time-based event expectancy paradigm. We followed previous work by Thomaschke et al. [56], which investigated time-based event expectancy in a slightly gamified approach.

3.1.1 Basic game mechanics. Figure 1 shows a screenshot from *Aim Lab* (left) and our custom game (right). When starting the game, the players are situated in a small virtual room - the game world. While in the game, players control the avatar's weapon movement by moving the mouse. The avatar is stationary and can not be moved in the game world. Players can fire their virtual weapon by pressing the left mouse button. The player's goal in the game is to shoot the appearing red spheres as fast as possible. The spheres spawn at five different locations: (1) middle, (2) left up, (3) right up, (4) left down, or (5) right down. Only one sphere is visible at any given time. The game starts with the middle sphere visible. After shooting the middle sphere, it is destroyed, and one of the lateral spheres (left up, right up, left down, or right down) appears. A distinct hit sound is generated upon shooting and destroying the lateral sphere before the middle sphere spawns again. If the player misses the lateral target, it gets destroyed as well; however, no hit sound will be played, and the middle sphere spawns. Players are rewarded with points for successful hits. On the contrary, they do not earn points if they miss the lateral target. This procedure is repeated until the game ends.

3.1.2 Experimental game mechanics. The experimental trial procedure is illustrated in Figure 2. A trial starts with spawning the middle sphere. After shooting the middle sphere (fixation target), it disappears, and the foreperiod begins. The foreperiod, in which no sphere is present, lasts 0.2 s, 0.8 s, 1.4 s or 2.0 s. After the foreperiod, the sphere spawns at one of the lateral positions (left up, right up, left down, or right down). The trial ends with the next shot regardless of whether the shot hits the lateral target. After an intertrial interval of 0.4 s, the subsequent trial starts. Crucial for our investigation is that the spawn time (foreperiod) of the lateral targets is not randomized (as it is in games such as *Aim Lab*) but manipulated through a specific correlation of foreperiod and spawn location to induce time-based event expectancy in players. While general probabilities of foreperiods (25 % 0.2 s, 25 % 0.8 s, 25 % 1.4 s and 25 % 2.0 s) and target location (25 % left up, 25 % right up, 25 % left down and 25 % right down) are equally distributed, the combination of spawn time and location is not. In 80 % of of all spawns, the a specific lateral sphere spawns after a specific foreperiod (e.g. 80 % of the left upper spheres spawns after 0.2 s). These frequent combinations are called valid time-target combinations. The counterpart to this are invalid time-target combinations: In 20 % of the spawns, this specific lateral sphere spawns after 0.8 s, 1.4 s or 2.0 s following a hit on the middle sphere. To prevent a potential bias induced by the spawn location of the lateral target, we counterbalanced the combinations of foreperiods and target locations across participants according to a Latin square (four different game versions). Figure 3 exemplifies valid and invalid trials for one round of one of the game versions. While playing, we measured players' reaction times to successfully hitting the lateral targets, their error rate and score. Crucially, in contrast to previous work on time-base event expectancy [54, 55] our experimental game mechanics employ four different time-target combinations. Previous work typically investigated implicit adaptation to temporal regularities using a binary scenario, i.e., two foreperiods paired with two target stimuli, to allow a clear distinction between valid and invalid combinations. However, to better reflect the large interaction space and complexity of nowadays' video games we used four combination pairs. In principle, this does not change the time-based event paradigm, but makes a implicit internalization cognitively more demanding.

3.1.3 Game procedure. The game procedure is illustrated in Figure 3. The game started with a short warm-up round (5 trials) to familiarize the players with the setting and the game itself. Following the warm-up round, participants played ten rounds (two practice rounds and eight experimental rounds), with each round consisting of 60 trials in randomized order. The first two rounds were set up as practice rounds in which participants implicitly learned the implemented time-target combinations. The remaining eight blocks were experimental rounds in which we hypothesized to measure the effects of the learned time-target combination. After each round, an in-game performance overview showcasing accuracy and the points obtained in the previous round was presented to the participants. Furthermore, the performance overview showed how the performance changed compared to the previous round, thus, motivating participants to beat their last score.

3.2 Experimental Design and Hypotheses

For our investigation, we used a 4 x 2 design with FOREPERIOD (*0.2 s, 0.8 s, 1.4 s* and *2.0 s*) and TIME-TARGET COMBINATION (*valid* and *invalid)* as within-subject factors. To measure potential effects of learned time-event-correlations on player performance we assessed two variables: (1) *RTshot* - reaction time to successfully hitting the

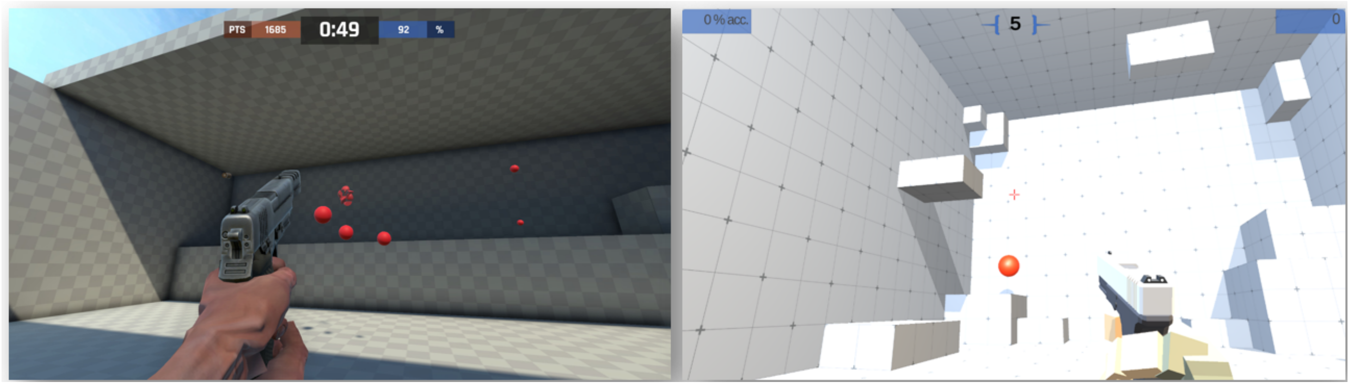

Figure 1: The left shows a screenshot from the aim trainer game *Aim Lab*. The right depicts a screenshot from our custom game. Both screenshots show the player's perspective, the player's virtual weapon, and game targets. Both games display additional performance information such as the points and the current accuracy.

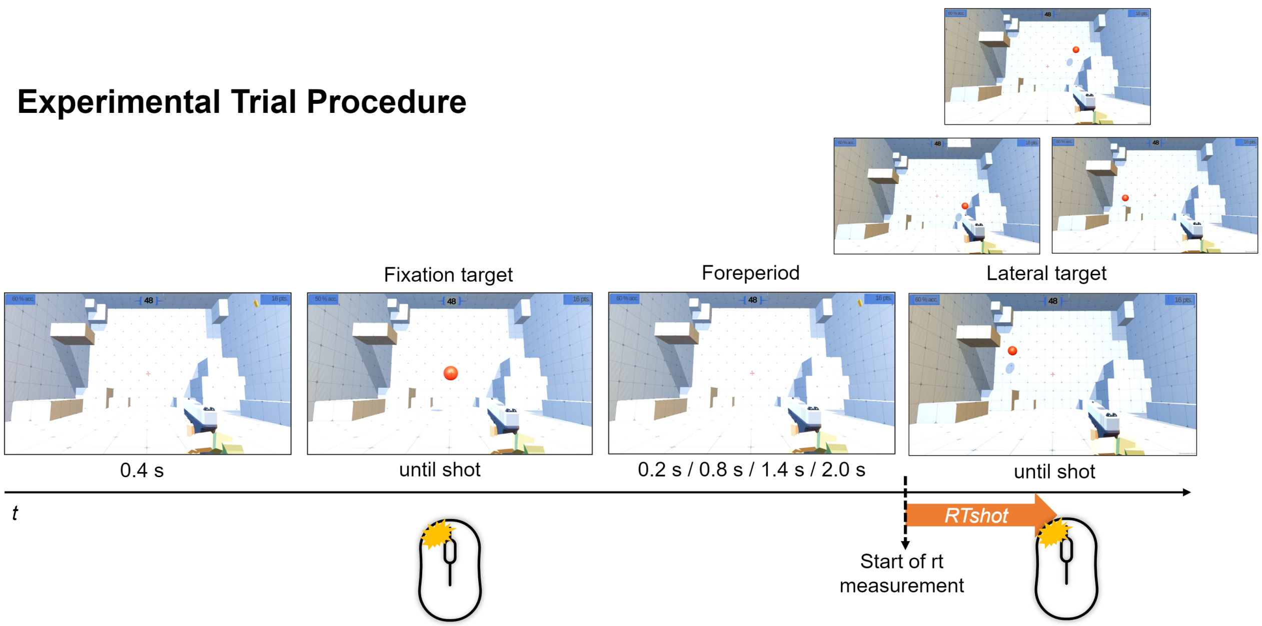

Figure 2: Illustrates the experimental trial procedure of the game. A trial starts with spawning the middle sphere. After shooting the middle sphere (fixation target), it disappears and the foreperiod begins. The foreperiod, in which no sphere is present, lasts 0.2 s, 0.8 s, 1.4 s, or 2.0 s. After the foreperiod, the sphere spawns at one of the lateral positions (left up, right up, left down or right down). The trial ends with the next shot regardless of whether the shot hits the lateral target. After an intertrial interval of 0.4 s, the next trial starts. *RTshot*, the reaction time to successfully hitting the lateral target after its appearance is denoted by an orange arrow.

lateral target after its appearance (orange arrow in Figure 2) and (2) *ERshot* - ratio of missed shots on lateral targets. If players indeed use in-game Time-Target Combination to anticipate target locations, we should observe faster reaction times (*RTshot*) in trials with valid compared to trials with invalid. Furthermore, we hypothesize that the error rate (*ERshot*) is lower in trials with valid trials Time-Target Combination.

3.3 Apparatus

We installed our game on a stationary workstation in our laboratory. The workstation (Intel i7, Nvidia GT970, 16 GB RAM) was attached to a monitor (24" FullHD @60Hz), a computer mouse (Logitech M10), and a headset. The game ran in full-screen mode. The laboratory was quiet and free of external disturbances.

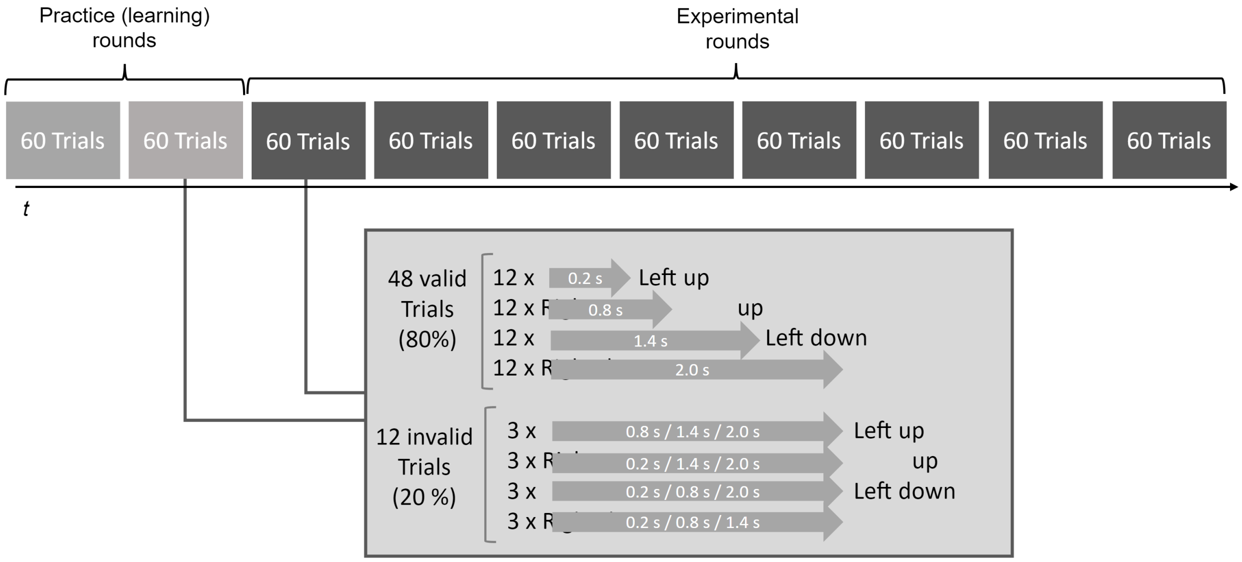

Figure 3: Depicts the game procedure and exemplifies the trial set of one game round of one game version. Participants played ten blocks each consisting of 60 trials. 80 % of the trials employed a *valid* and 20 % an *invalid* Time-Target Combination. In the depicted version 80 % of the left upper targets spawn after 0.2 s, 80 % of the right up targets spawn after 0.8 s, 80 % of the left down targets spawn after 1.4 s and 80 % of the right down targets spawn after 2.0 s. In 20 % of all spawns the lateral target spawns after one of the remaining foreperiods. The order of trials (*valid* and *invalid*) was randomized.

3.4 Procedure

Upon arrival, participants were greeted at our laboratory by the experimenter. Participants were not informed about the exact purpose of the study (investigating time-based event expectancy in video games) but were told to test a novel game. After giving informed consent and agreement to data collection, they were informed about the study's procedure. Then, each participant played the game. Upon finishing the tenth round (two practice rounds and eight experimental rounds), the game closed automatically and opened a post-experience questionnaire. The questionnaire was used to collect demographic information from the participants, such as their identified gender, age, need for eyesight correction, state of employment or course of study, information about their experience with video games, and information about their experience with working on a computer in general. Participants rated their experience with video games and computers on a scale based on weekly hours spent (0 - 3 hours, 3 - 5 hours, 5 - 10 hours, 10 - 15 hours, and more than 15 hours). The study was concluded with a debriefing, in which the participants were asked about the temporal pattern of the game and whether they noticed any temporal regularities. In the debriefing, the experimenter first asked whether the participant noticed any regularities in the game. The debriefing was finished if the participant stated that they did not notice any regularities. On the other hand, if the participant stated that they noticed regularities in the game, the experimenter asked what the noticed regularities were. Then the experimenter asked if the participant noticed any temporal regularities and if the participant could state what these temporal regularities were. After these three additional questions, the debriefing was finished as well. The experimenter noted all given answers on a beforehand prepared form. The study lasted about one hour and received ethical clearance via the research ethics policy of our institution.

3.5 Participants

We recruited 28 participants via mailing lists of our institution. Since we investigate implicit adaptation to in-game Time-Target Combination, we excluded three participants whose responses in the debriefing indicated that they explicitly noted the temporal regularities of the game. In summary, this leaves data of 25 participants for analysis. This sample size still ensured a power of $1 - \beta > .90$ [16, 17] to detect an effect size η_p^2 of at least 0.2 for the relevant main effect of (an effect size that is below the effect sizes reported in related work [2, 57, 58]). The remaining participants' ages ranged from 20 to 27 years, with an average age of 23.44 years (SD = 2.10 years). All participants were right-handed and had perfect or corrected eyesight, which was a requirement for participation. The majority of participants, 18 of 25 reported they do not play first-person shooter games at all or for a maximum of three hours per week. Two participants reported playing first-person shooter games for 3 to 5 hours per week, three reported 5 to 10 hours per week, and two reported more than 15 hours per week. All participants were students at our institution and were compensated with one credit point for their course of study.

3.6 Statistical Analyses

Raw data and analysis scripts are available via OSF. Data was analysed in R (version 4.2.3, [44]) using within-subject ANOVAs and

t-tests (R package *rstatix* version 0.7.2; [30]). Effects with violations of sphericity were Greenhouse-Geisser corrected and are reported with corresponding ε estimates.

4 RESULTS

In line with previous work investigating time perception [7] and time-based event expectancy [55], we excluded the warm-up phase and the first two rounds of the game from the analysis. The warm-up phase was solely implemented to allow participants to familiarize themselves with the study setup and the game. In the first two rounds of the study, the participants had not had enough playtime to implicitly internalize the time-event correlations of the game yet. Therefore, the effect of anticipated game events based on in-game Time-Target Combination should evolve in later blocks (experimental blocks). Further pre-processing of the data is described in the respective section for each measure. In the following, we first describe the results of the experiment's debriefing. Then we continue to analyze the data of *RTshot* and *ERshot*.

4.1 Debriefing

Twenty-one participants stated that they noticed some regularity in the game in the debriefing. However, nine answers were related to the middle target and that it always spawned in alternation with the lateral targets. The remaining twelve participants reported noticing some temporal regularities related to the game. Out of those twelve answers, four replies were not related to the actual temporal pattern of the game. One participant, for example, stated that the interval between targets was randomized, and one participant felt that the targets appeared in a rhythm. Only eight answers out of the twelve participants that stated that they noticed a temporal regularity in the game indicated that the participant was aware of the temporal pattern of the game. Six participants stated that they felt that each target's appearance differed. One participant also reported some temporal relation between side and spawn duration, and one participant stated that they sometimes had to wait for new targets to appear. None of the analyzed participants could pinpoint the temporal regularities of the game precisely.

4.2 RTshot

This measure describes how long it took participants to shoot the lateral target after its appearance (see orange arrow in Figure 2). For the analysis of *RTshot*, we excluded trials in which participants failed to hit the lateral target (12 % of all trials). The exclusion of failed shots was necessary since we cannot calculate *RTshot* if players did not successfully hit the target. We then excluded trials with reaction times higher than 4000 ms (0.2 % of all trials) as an extremely high reaction time may indicate a distraction of the participant. In accordance with related work [8], we then excluded all trials with reaction times that deviated more than three standard deviations from the individual condition mean (1 % of all trials). In sum 86.8 % of all experimental trials were included for *RTshot* analysis.

Figure 4 (A) shows mean *RTshot* values as a function of Foreperiod x Time-Target Combination. A 4 (Foreperiod: *0.2 s* vs. *0.8 s* vs. *1.4 s* vs. *2.0 s*) x 2 (Time-Target Combination: *valid* vs. *invalid*) ANOVA with repeated measures on both factors on *RTshot* revealed a significant main effect of Time-Target Combination, $F(1,24) = 11.27$, $p = 0.003$, $\eta_p^2 = 0.32$. Participants performed significantly better in trials with *valid* time-target combinations than in trials with invalid combinations (969 ms vs. 1001 ms, Figure 4C). Neither the main effect of Foreperiod, $F(1.45,34.83) = 2.55$, $p = .107$, $\eta_p^2 = 0.10$, $\varepsilon = 0.484$, nor the interaction effect Time-Target Combination x Foreperiod $F(3,72) = 0.73$, $p = 0.537$, $\eta_p^2 = 0.03$ was significant.

4.3 ERshot

ERshot measures the ratio of failed shots on the lateral targets and is specified in percent. Figure 4 (B) shows mean *ERshot* values as a function of Foreperiod x Time-Target Combination. A 4 (Foreperiod: *0.2 s* vs. *0.8 s* vs. *1.4 s* vs. *2.0 s*) x 2 (Time-Target Combination: *valid* vs. *invalid*) ANOVA with repeated measures on both factors on *ERshot* did not reveal a main effect of Time-Target Combination, $F(1,24) = 1.52$, $p = 0.229$, $\eta_p^2 = 0.06$ (Figure 4D). The main effect of Foreperiod was significant, $F(2.15,51.51) = 4.64$, $p = 0.012$, $\eta_p^2 = 0.16$, $\varepsilon = 0.715$. However, post-hoc pairwise t-tests with Bonferroni-correction for multiple comparisons did not reveal any significant differences between the error rates for different foreperiods (all $p > .064$). The interaction effect Time-Target Combination x Foreperiod $F(3,72) = 0.62$, $p = 0.606$, $\eta_p^2 = 0.03$ was not significant.

5 DISCUSSION

Our study provides evidence for the relevance and applicability of time-based expectancy in games and shows that players implicitly use elapsed time as a predictive cue to anticipate game events. Based on the implemented target-time combinations, players built time-based event expectancy that influenced gaming behavior and performance. Players' performances increased in trials with valid time-target combinations, i.e., they shot targets faster than in trials with invalid combinations. However, error rates were not influenced. Notably, the found effects do not reflect a strategic behavior. None of the analyzed participants explicitly noticed the implemented temporal regularities of the game. Since none of the participants was consciously aware of the temporal patterns of the game, they could not be part of an applied strategy.

In this section, we discuss our findings and refer to prior work, predominately from cognitive sciences investigating time-based event expectancy to contextualize the found effects. Additionally, we discuss novel effects not yet investigated in previous work regarding game design and player behavior. We continue to discuss the implications of our findings for researchers, game developers, and gamers. We conclude with the limitations of our work and show how future work may continue to explore time-based event expectancy in video games.

5.1 Effects on Reaction Time

Our findings regarding the reaction time to shoot targets extend previous work. Thomaschke et al. [56], for example, showed that reaction times in valid time-event combinations are significantly shorter than reaction times in invalid combinations. Similarly to our work, the authors did not find significant effects on the error rate. Interestingly, in our work, we revealed a large effect [45] ($\eta_p^2 = 0.32$) of time-based event expectancy on the reaction times. The found effect is even larger than effects found in related strictly controlled

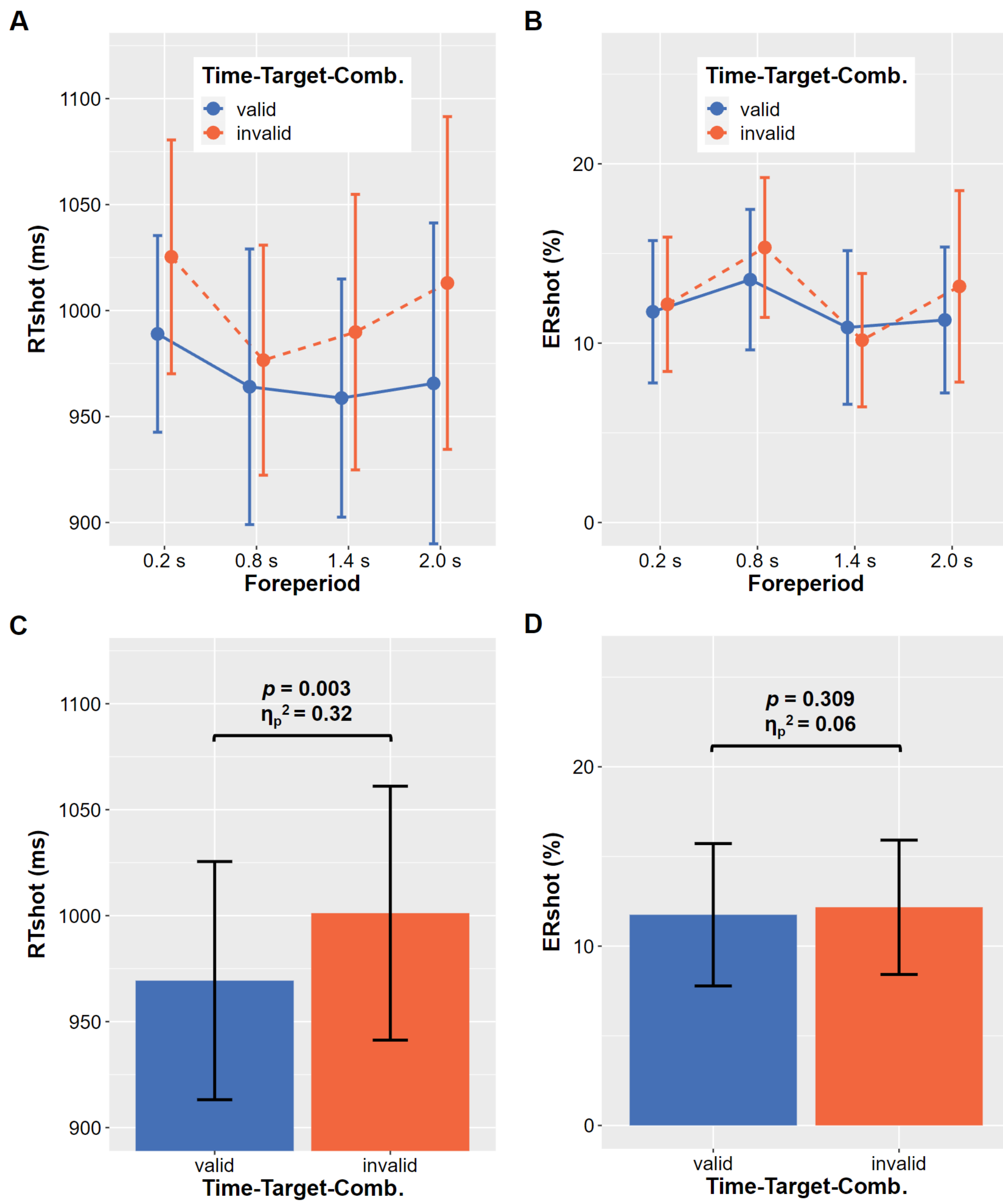

Figure 4: Upper Panel: Mean reaction times of successful shots on a lateral target (*RTshot*, A) and mean error rates (*ERshot*, B). Data is shown as a function of Time-Target-Combination: valid (blue solid lines) vs. invalid (orange dashed lines) and Foreperiod: 0.2 s vs . 0.8 s vs. 1.4 s vs. 2.0 s (X-axis). Lower Panel: Main effect of Time-Target-Combination for *RTshot* (C) and *ERshot* (D). Participants achieved significantly shorter reaction times in trials with valid combinations than in trials with invalid combinations (C). Results of *RTshot* show that players implicitly adapted to time-event correlations and thus utilized the game's temporal regularities subconsciously. Error rates were not significantly influenced by the validity of Time-Target-Combination (D). Error bars represent the 95 % confidence interval of the means.

psychology experiments (η_p^2 = 0.11 [64] and η_p^2 = 0.26 [56]). The large effect size is surprising because we initially argued, in line with previous work [40, 47], that games may hamper the ability to form time-based event expectancy. Generally speaking, video games confront players with more information and interaction than a controlled psychological experiment. Instead of just pressing a single button on a keyboard initiated by a target signal, players in our game had to actively move the crosshair in two dimensions to select the targets. Furthermore, the players had to constantly process additional visual and auditory information, such as weapon movement, score, score changes, and game sounds. In principle, this additional information should lead to an increased cognitive load and may hinder the internalization of temporal regularities. Our work, however, shows that playing video games does not suppress the players' ability to implicitly adapt to time-target combinations. In addition, it is important to note that the large effect was observed in a scenario with four time-event correlations, which presents participants with a even more cognitivly demanding scenario compared to previous work that tested two [55, 58] or three time-event correlations [2]. Exploring time-based event expectancy beyond two or three time-event correlations is crucial for it to be pragmatically applicable in video games and their large interaction space.

5.2 Implications for Play and Research

Our work has implications for game developers and video game researchers. Game developers might utilize our findings in game design. For example, they could adjust the game's difficulty by adjusting the temporal regularities found in the game. On an easy level, the game, for instance, could employ strong time-target correlations and thus allow the players to form time-based event expectancy, ultimately increasing the performance and lowering the overall difficulty. On the other hand, game designers could explicitly prevent players from forming time-based event expectancy by disturbing the temporal predictability of the game mechanics. Preventing players from forming a temporal model of the game would eventually lead to reduced performance and increased difficulty. This increase or decrease in difficulty directly influences the players' performances and, in turn, may alters the players' experiences according to the performance-enjoyment link discussed in previous work. This work investigates if players who are performing worse experience less enjoyment and vice versa [31]. Hence, applying temporal regularities in video games may also alter the players' gaming experiences.

Moreover, our work shows that time carries information, besides its numerical value, in video games. We show that players can internalize temporal information to adapt their behavior. Game developers can build upon those findings to provide, for example, a consistent interaction that does not violate the expectations of the players with the game. One example is implementing a user interface (UI) based on time-based event expectancy. Previous work investigating user interactions with a website [66] found that users benefit from a temporally consistent UI. As we showed that video games do not suppress the ability to form temporal expectancy, the same approach may be used to improve player-game interaction. Other ways to utilize our findings in video games may be through integrating time as a game element. Knowing that players form implicit expectations about game events may enable game developers to play with these expectations to alter game experience. Similarly to work investigating long-term uncertainty in video games [42, 43], knowledge about time-based event expectancy may be used to integrate short-term surprises in video games. Knowing that players form implicit expectations about temporal regularities in a game may allow developers to alter them. For example, developers could change the temporal component of quick-time events in game series such *God of War* or *Uncharted* to either validate or break with players' expectations to keep player engagement high. In shooting games certain in-game mechanics could be tied to temporal regularities and irregularities, similar to *Returnal*'s reloading mechanism [63].

In addition to time-based event expectancy as a tool to manipulate player-game interaction, our findings also open other avenues to improve the game design. For example, cloud gaming providers could build upon the information provided by this work to increase the stability of the gaming experience in high-latency systems. Cloud gaming services allow players to instantly play almost any game on almost any device by streaming the game via the Internet. However, due to the heavy network communication required, cloud gaming services are affected by high latency [25, 51]. This latency, in turn, leads to a significant decrease in player performance and gaming experience [11, 33, 34]. Partly, this may be because high latency, especially strongly fluctuating latency such as jitter, destroy the temporal predictability of the game and thus prevents players from forming strong time-event correlations. By embedding mechanics to enable players to build time-based event expectancy, for example, by scheduling game events following latency as proposed by Thomaschke et al. [55], cloud gaming could attenuate the adverse effects of latency. Scheduling game events and a consistent game interaction, for example, could be achieved by artificially adding latency to create a stable and invariant gaming environment.

Our findings are valuable to other video game researchers. Ultimately, video game researchers aim to understand players, the game itself, and the interaction between player and video game. Understanding human behavior is crucial in this kind of research. For decades psychology has investigated human behavior, cognition, and interaction. Video game researchers benefit from this reservoir of knowledge. Our work exemplifies that utilizing previously found phenomena in cognitive sciences could further deepen our knowledge about players, video games, and the way players interact with games. One example of a cognitive concept studied in psychology that is also relevant to video games is binding and retrieval of perceptual and action features [18, 28]. Binding research has already demonstrated that our cognitive system momentarily links temporal information with other internal and external information, which has consequences for subsequent actions [7, 41]. Similarly, one could investigate how the temporal features of the game environment are integrated into player's perception and action planning and how this is reflected in player behavior and performance.

5.3 Limitations and Future Work

Our work induced time-based event expectancy based on time-target combinations in an aim trainer game. While aim trainers comprise fundamental game mechanics of FPS games, such as target tracking and selection, they lack other game elements, such as a story or player movement. Thus, while essential concepts can be translated to the FPS genre, our findings may be less significant in more complex video games, in which players have to move around in a game world, process visual and auditory, and have to defend themselves from opposing entities. Additionally, it is also possible that our findings do not generalize to all video game genres. However, recent work showed that the effects of latency are independent of the video game's in-game perspective [22]; thus, it is likely to assume that other temporal components of video games, such as time-based event expectancy, generalizes to other gaming scenarios. While the game we used in our study already drastically increases the ecological validity of our findings compared to fundamental psychology experiments, it still is a highly controlled study apparatus. Hence, future work should investigate if our findings generalize to more ecologically valid games and other genres. In the same vein, future work should investigate other in-game mechanics coupled with temporal elements. In our work, we coupled the location of targets to certain foreperiods. However, this is not the only possibility. Future work, for example, could investigate how map awareness in a game such as Counter-Strike 2 interacts with temporal expectations. In Counter-Strike 2, two teams fight each other for an objective. Often, these fights are won by well positioning the own team and knowing when and where enemies could appear. If, for example, no enemy appeared at a certain location after a certain duration, the team needs to take into account that the enemies could attack from another location and prepare for this attack accordingly. This switch in preparation for an enemy attack, is tied, although not only, to a temporal component.

Another limitation of our work may be the methods used to incentivize participants to perform as well as they can. After each round, we implemented a scoring system and presented a performance overview showing how participants' score and accuracy changed compared to the previous round. However, our work does not elucidate if the implemented methods motivated the participants. Thus, future work should investigate if video game players can be motivated by comparatively simple performance statistics while establishing a time-based event expectancy.

Furthermore, our work does not elucidate the link between time-based event expectancy and game experience. However, previous work indicates that the game experience alters the subjective time perception [40, 47]. Thus, future work should investigate how time-based event expectancy and game experience affect each other. On the same note, while we showed that a stable temporal environment allows players to increase their performance, it is also possible that this internalization leads to performance degradation if the temporal regularities suddenly change, for example, induced by an abruptly changing latency. Hence, future work should also investigate if time-based event expectancy leads to performance degradation in unstable environments.

Lastly, we investigate four distinguishable foreperiods, 0.2 s, 0.8 s, 1.4 s, and 2.0 s, to allow players to implicitly learn the target-time combination. We choose the tested foreperiods based on previous research investigating time-based event expectancy in fundamental psychological work. However, it remains unclear how close together foreperiods may converge to still allow the formation of time-based event expectancy. Related work does not specify how long the foreperiods must be to allow implicit learning of the regularities. Future work, thus, should investigate how long the difference between foreperiods and how long the foreperiods themselves have to be to still allow the implicit formation of time-based event expectancy. Since we found a substantial effect in our work, researching these questions with video games is promising.

6 CONCLUSION

Despite its promising application in altering game experience and player performance, it previously was unknown if the time-event correlation paradigm translates to video games. In this paper, we present a novel approach to investigating time-based event expectancy in the context of video games. We developed a 3D video game and coupled its game mechanics with time-target combinations, allowing players to internalize the game's temporal regularities. We then conducted a study and analyzed the data of 25 participants. We found that players can use the game's temporal regularities to increase performance. Thus, we demonstrate the robustness and feasibility of the time-event expectancy paradigm outside of highly controlled psychological experiments. We found that players had significantly shorter reaction times when the target stimuli followed a valid time-target combination.

In summary, we found that players form strong temporal models about the game's regularities and are thus able to increase their performance. With our work, we aim to inspire researchers in both psychology and video games to increase their collaboration. Furthermore, we show that time-based event expectancy may be a suitable method to practically regulate different game mechanics, such as the game's difficulty. Finally, our work shows that time in video games carries more information than its mere numerical value. Players in our study implicitly adapted their behavior to our game's temporal regularities, resulting in increased performance. Our work provides the first step to a novel approach to time in video games.

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