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2026

Original citation:
Johanson, C., Wessels, H., & Friehs, M. A. (2026). Watching to win: When watching others play improves performance. *Entertainment Computing*, *56*, 101067. https://doi.org/10.1016/j.entcom.2025.101067

Entertainment Computing 56 (2026) 101067

Contents lists available at ScienceDirect

Entertainment Computing

journal homepage: www.elsevier.com/locate/entcom

Watching to win: When watching others play improves performance

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ARTICLE INFO

Dataset link: https://osf.io/fxa9c/files

Keywords:
Videogames
Observational learning
Skill acquisition
Performance
Game design
Streaming

ABSTRACT

Despite gamers' widespread use of observation as a learning strategy, the overall effects of observational learning on in-game performance and conditions for effectiveness are underexplored. We investigated whether and how observation improves gaming performance through two controlled studies using a Super Hexagon clone. Study 1 (n = 23) examined player-observer pairs; Study 2 (n = 69) systematically varied observation content (same vs. randomized obstacle sequences vs. playing instead of observing). Results showed that observers significantly outperformed players when comparing performance after equal play time, in-person and via video, but only when observing the same obstacle sequence. When comparing final performance, playing yielded greater overall improvement than observing. These results provide empirical validation for observational learning in games while identifying sequence-specific observation as an important factor in digital contexts, offering insights into how players and designers can incorporate observation into learning strategies and game design.

1. Introduction

Mastering videogame skills typically requires extensive practice, but many players supplement this practice by watching others play. Gamers now spend more time watching game-related content (8.5 hours/week) than actively playing (7.4 hours/week) [1], with platforms like Twitch delivering 3.3 billion hours of gaming content in Q1 2024 alone [2]. Many viewers believe that watching others can help them learn new strategies to improve their own gameplay [3,4]. Yet despite this widespread interest in observational learning, empirical evidence for whether observation actually improves gaming performance remains surprisingly limited. Prior experimental research on learning in-game skills has focused almost exclusively on active practice (e.g., [5–8]), leaving fundamental questions unanswered about what players can learn from observation alone.

The potential that observational learning could be an effective strategy for learning and improving at games could have practical applications for both players and game designers, given how central skill development is to many gaming experiences. Learning a game and overcoming its challenges is a strong source of intrinsic motivation for players — players can be highly motivated to keep playing games if those games continue to provide an interesting challenge [9]. However, repeated failure can also lead to frustration and abandonment [10], highlighting the importance of both maintaining challenge while supporting the player's success. If observational learning is a genuine supplement to active practice, games could be designed with this in mind, provide additional pathways to onboarding and skill development — ones where players could temporarily take on a passive role to better prepare for challenges, reducing the stress of repeated failure that can deter players from challenging games [10] while preserving the motivational benefits that come from successfully overcoming those challenges.

Despite the widespread belief that observing others play is an effective method of learning, empirical evidence for its effectiveness is limited. While qualitative research has extensively documented players' motivations to learn through observation [4,11], there is little empirical evidence that this learning approach will translate into actual in-game performance gains. It is not clear if, when, or why observational learning works in gaming contexts.

The concept that it is possible to learn new behaviors by watching others [12] is well established in other domains. In particular, in sports psychology (where studying the performance of athletes is essential) decades of controlled experiments have established the efficacy of observation and isolated its mechanisms [13]. This research has demonstrated that athletes can learn specific movement strategies [14], spatial sequences [15,16], and timing [17] through observation. These findings appear particularly relevant to gaming contexts, as both sports and games involve developing perceptual-motor skills and strategic thinking under the pressure to perform [18,19], suggesting that the

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https://doi.org/10.1016/j.entcom.2025.101067
Received 6 June 2025; Received in revised form 1 October 2025; Accepted 4 December 2025
Available online 5 December 2025

findings should transfer to games. However, this similarity could be misleading.

Several key differences between sports and games provide reason to suspect that observational learning might work differently in videogames. First, while athletes observe and can directly reproduce physical movements, gamers observe on-screen actions performed through an input device (e.g., a keyboard, mouse, or controller) and therefore must translate on-screen events to specific inputs. This may affect stimulus–response compatibility as the association between the on-screen action and the response is not as natural as in the physical realm [20]. Second, digital games are able to present perfectly identical challenges across multiple attempts, compared to physical environments, where there is naturally more variation in each attempt. This creates an opportunity for sequence-specific observational learning [15,16], the learning of which may be aided due to the identical conditions present during observation and subsequent attempts [21]. Third, games provide immediate and precise feedback, which differs considerably from the feedback found in sports, which could be delayed or difficult for novices to understand [13]. Observational learning in sports is often used to help athletes learn how to identify errors [22,23], and this may not be as necessary in digital contexts where feedback is already clear. This could mean that simply playing the game is a better learning strategy than observation. Fourth, in sports, there is more likely to be a separation between play and practice, and sports research examines athletes engaged in deliberate practice, which involves effortful attention and a specific intention to improve [24]. Outside of structured competition and esports [25], games are played for pleasure. While athletes may be prepared to closely scrutinize a model's performance [13], gamers playing for entertainment may direct the same amount of attention to learning. These differences raise questions relating to whether the findings from sports psychology will indeed transfer to gaming contexts.

To explore this possibility, we conducted two studies. In the first study, we invited pairs of participants to play and watch a clone of the game, *Super Hexagon*, a game which has players rotate around a central point to avoid incoming obstacles. One of the participants was assigned to be a "player" and the other an "observer". Both participants separately completed a five-minute play session to determine baseline performance in the task. Next, the player completed three additional five-minute play sessions separated by one-minute breaks while the observer watched. To isolate the effects of visual observation on learning from verbal instruction, we instructed participants to stay silent during gameplay; however, we did allow participants to speak to one another during breaks in order to explore the social dynamics that emerge during collaborative play.

In the second study, we invited participants individually to play Super Hexagon with or without observing a recorded video. To investigate whether sequence learning was a factor in learning the game, we had three groups: a "player" group where participants played for four sessions without any opportunities for observation, or one of two "observer" groups where participants played for one session, then watched a pre-recorded video of another player playing, then played one more session. The two observer groups differed only in the video that was watched; one group watched a video featuring the same level they were playing, while the other group watched a video featuring a variation of the level where the obstacle order was randomized so that every attempt within the recording showed a unique sequence of obstacles. To fully isolate the effects of observation from verbal instruction, the video did not feature any commentary.

The aim of both studies was to assess whether observational learning can be applied as a tool to help players improve at the games they play, and to perform an initial investigation into how observational learning might differ from sports contexts. Based on the related work on observational learning in sports psychology we formulated the following hypotheses:

- **H1:** All groups will improve at the game over time. (Study 1 and 2)
- **H2:** With the same total play time, observers will outperform players. (Study 1 and 2)
- **H3:** Time spent playing the game will yield more performance improvements than time spent watching. (Study 1 and 2)
- **H4:** Watching a video with the same sequence of obstacles will be more effective for learning than a video with a randomized sequence of obstacles. (Study 2)

Furthermore, we also verified that our players started out with similar levels of performance and that both groups improved over time. We also included exploratory analyses to better understand how players interact with one another while watching and playing together and how players subjectively experience skill improvement within the game.

We found clear evidence that observational learning can benefit video game performance. Our controlled experiments showed that observation directly led to immediate performance gains. These gains were contingent on whether the observed gameplay closely matched the upcoming challenge. In particular, whether the exact sequence of obstacles being observed was necessary for successful transfer — viewing a random sequence of obstacles provided less benefit. Our first study additionally revealed the important social dimension of observational learning in gaming contexts. When given opportunities to interact, player-observer pairs naturally engaged in strategy discussions and coaching behaviors, suggesting that the social aspects of watching others play may be as important as the observational learning itself.

This work provides a controlled examination of the effectiveness of observational learning in videogames, with implications for both players seeking to improve their skills and game designers looking to better support player development. Our findings establish baseline evidence for observational learning mechanisms in games, providing insights for players and game designers about when and how observational learning can supplement practice, while opening questions for future research into how these effects might generalize to other gaming contexts. With game difficulty being a key reason for engagement as well as a potential cause for abandonment, observation stands out as a promising pathway for developing skill beyond simple repetition.

2. Related work

Observational learning is the idea that one can learn a skill by observing a live or pre-recorded demonstration [26]. The theoretical foundations of observation as a form of learning are well established, with early work establishing that mimicking others is an effective way to learn new behaviors [12,27]. This was extended by sports psychology researchers, who studied the applications of this in athletics via controlled experiments [13]. In this section, we discuss how players are already using observational learning, why observational learning works in non-gaming contexts, the factors affecting observational learning, and relevant findings from prior research studying learning game skills through observational learning.

2.1. Watching to learn

Today, millions of users watch others play games online, via platforms such as Twitch [28]. People choose to watch games rather than play them themselves for a variety of reasons, such as the desire for entertainment, the desire to release tension through distraction or relaxation, the desire for recognition of one's contributions in the chat, the desire for enhanced social connections, or the desire to learn more about a game or strategies used within a game [4].

Past work has explored how players watch esports (a subset of gaming focusing on competitive play [25]) to learn about a game (e.g., [3,29]). In this context, one of the main reasons players give for spectatorship is to acquire new knowledge about the game [29];

players want to see how players better than themselves are playing the game [3]. Newer players who want to get into these types of games will watch streams of casual (non-professional) players to gain an understanding of the basics, whereas experienced players turn to streams featuring more skilled (often professional) players to learn about strategies in use by these players [3,4].

2.2. How observational learning works

Observational learning has been studied extensively in contexts other than digital gaming, and in particular, has been demonstrated to be an effective method of skill learning in sports [30,31]. In research, esports and traditional sports are frequently compared due to the similar skills used [32,33]. Esports games are simply a type of digital game [25], and the skills found within digital games are similar to traditional sports. These include perceptual-motor skills, hand-eye coordination and several cognitive skills, for example, pattern recognition [34,35].

Research on perceptual-motor skill learning has identified several things that can be learned by observing a model perform a skill. Specific movement strategies can be conveyed through demonstrations. For example, learners were found to model the specific strategy demonstrated by a model [14,36]. Additionally, observation can help with pattern and error recognition — observing allows one to learn from the mistakes of others without the learner needing to make those mistakes themselves [37–39]. Spatial information and specific sequences [15,16] can also be learned through observation. For example, one can learn sign language by modeling another making specific signs [40]. More advanced examples of this approach being successful include learning ballet sequences [41], specific skiing actions [42], and surgical techniques [43].

2.3. Factors affecting observational learning

Several factors affect the efficacy of observational learning. These factors include the model, the learner, the training environment, and the task itself.

Prior research (e.g., [22,44–46]), has looked at the efficacy of novice versus expert models demonstrating the skill; these models vary primarily in terms of the number of mistakes they make when executing a skill. Two of these studies [44,45] compared no demonstration to a demonstration by either a novice or an expert and found that *any* demonstration was beneficial for learning, regardless of the expertise of the person demonstrating the task. Later work found that a combination of viewing novice and expert demonstrations was more efficacious than either demonstration on its own [46]. Aside from the actual expertise of the model, the perceived competency of the model is important; if a model is seen as competent, then the likelihood of imitation is increased [47]. Additionally, the similarity of the model also plays a role; a model who is similar to the learner (for example, in age or gender), can positively affect observational learning, as it can enhance the sense of relevancy and connection to the behavior shown [47].

Other past research has looked into modifying the training environment by providing additional feedback (specifically, knowledge of results) alongside the demonstration. This work found that the presence of knowledge of results had more of an effect on learning than the expertise of the model performing the demonstration [22]. This could be because the additional feedback gave the learner information that allowed them to understand what they were seeing. A later experiment [23] found that telling a learner about what they were about to see demonstrated *before* the demonstration was more effective for learning compared to giving the learner the same information *after* the demonstration. This allowed learners to detect errors as they were occurring in the demonstration and better understand what they were observing. This could be because an observer engages similar cognitive processes as the person carrying out the task, and so can use knowledge of results to improve their internal representation of the task [48] and ability to detect errors [37,38].

The complexity of the task may also affect the efficacy of observational learning. Several studies tested observational learning in the context of a serial reaction time task. Some (e.g., [49]) found that observational learning did not occur when observers watched a complex sequence. However, follow-up studies showed that it *is* possible to learn complex sequences through observation [16], if the sequence is salient (it is obvious to the learner that there is a specific sequence), and if the learner can give the task their full attention (i.e., there are no "dual task demands"). Wulf et al. [50] suggest that observational learning is more effective for complex skills than simple skills. They argue that there are more possible aspects to observe in a complex task, that observation may afford a learner with an opportunity to extract information about the task that they would not be able to access while performing the task themselves, and that allowing learners time to observe may additionally act as rest periods in a training schedule, allowing learners to benefit from spaced practice, an alternative training technique that has been shown to benefit performance [51,52].

Finally, the mood of the learner can play a role in the efficacy of observation. A positive affective state can improve focus and attentiveness, allowing an observer to better focus on the model and the specifics of the tasks [53]. Conversely, a negative affective state can result in the focus of attention being more selective and narrow. This might negatively affect which behaviors are noticed and recalled.

2.4. Observational learning and games

Qualitative research has documented the phenomenon of watching others play video games. Researchers have consistently found that learning from others is a primary motivation for game viewing, alongside entertainment and social connection [4,11,54]. For example, studies on the motivations of Twitch users and communities that have developed on Twitch have found that learning is an explicit goal of many viewers [4,11]. Aside from live broadcasts, pre-recorded "let's play" content has also been considered as a method for learning how to play [54], in particular as a pedagogically useful "think aloud" activity [55]. Observation is commonly combined with peer learning and mentoring, with dedicated communities emerging as a result [11,54]. In general, viewers actively seek out skilled players to observe, engage in strategy discussions in chat and forums, and integrate what they observe into their own gameplay. Similar experiences have also been observed in in-person interactions; for example, one study of siblings found that siblings scaffold one another to learn how to play, with more experienced siblings sometimes playing the game while the other watches [56].

While observational learning has been empirically studied in other domains, few empirical experiments have investigated the effectiveness of observational learning as a strategy for learning how to play video games. One early study by Pollock and Lee [44] tested the effect of watching another play a game on performance in Microsoft's *Olympic Decathlon* game from 1982 [57]. Participants watched either a novice or an expert play, or neither. They found that the two groups that watched another player before playing themselves achieved a significantly higher level of performance compared to the group that did not watch another player; however, whether or not an expert or novice was watched made no difference.

Another manuscript by Payne et al. [58] explored observational learning in the context of learning a specific skill from a game. It looked at the factors involved in learning from an instructor via video, and the presence of chat features commonly found on online platforms such as Twitch and YouTube. In particular, it looked at the expertise of the instructor, the presence of instructor–learner interaction, the presence of learner–learner interaction (i.e., a chat feature), and the difference between live-streamed video and pre-recorded video. Players were instructed on the skill of last hitting in *League of Legends* [59]. They found that extroverts benefited from learner–learner interaction, that learner–learner interaction was important when the instructors were novices, and that novice instructors were as effective as experienced instructors.

Payne et al. [58] suggest that the reasons for learning differed depending on the instructor's expertise. When watching a novice instructor, they learn from the mistakes that the novice is making to improve their own performance. However, experts, having experience with many variations of the task, provide knowledge and explanations that are more abstract to cover possible variations. This is in contrast to the novices, who tend to explain how to complete tasks in a more concrete way [60]. Importantly, however, Payne et al.'s study examined observational learning in the presence of verbal instruction and chat interaction, making it difficult to isolate the specific contribution of visual observation from verbal instruction.

In sports, an important factor that affects the efficacy of visual observation is whether it is combined with verbal instruction [61]. This is commonly done in gaming contexts; for example, streaming platforms combine visual observation with verbal commentary and chat between viewers [11]. These verbal elements may enhance learning while simultaneously making it difficult to determine whether performance improvements stem from visual observation of the on-screen action or some form of verbal learning. However, the gaming domain also includes other scenarios which may not feature any verbal component; for example, reviewing a replay of a match or watching a speedrun attempt. In other cases, the observation occurs within the game itself, for example, one player may spectate another [62]. The visual observation may also be viewed from a different perspective, for example, by following a "ghost" — a common feature of many racing games such as *Gran Turismo 7* [63].

2.5. Summary and gap

The literature presents a paradox. Observational learning is a mature and well-validated theory [13], gaming culture has extensively adopted practices that resemble observational learning via platforms like Twitch and YouTube [4,11], and the games industry has incorporated many observation-supporting features like spectating modes and replay systems. Yet, only two experimental studies exist to provide evidence for its efficacy in gaming [44,58], leaving many important theoretical questions unanswered.

Without understanding what can be learned through pure observation, or the possible circumstances where it does or does not occur, game designers cannot design effective observational learning experiences, and players cannot make informed decisions about when they should be actively practicing or supplementing their practice with observation. Our research addresses these gaps through two controlled experiments that establish whether observation is a viable learning strategy in general, whether the efficacy of observation is affected by the similarity of the viewed challenge, and whether a player's time is better spent actively practicing or observing. This approach provides foundational empirical evidence for how observational learning operates in digital game contexts, establishing a basis for future work examining how verbal elements, social interaction, and other factors might enhance or modify these core observational learning effects.

3. Methods and materials for both studies

3.1. The game

The experimental task that was given to the participants was a clone of the game *Super Hexagon* [64] (originally developed by Terry Cavanagh), illustrated in Fig. 1. The game's objective is to avoid hitting the constantly approaching obstacles by turning either clockwise or counterclockwise. Rotation is controlled by the arrow keys on the keyboard, which serve as the only input needed for the game. Given its simplicity, the game offered a low cognitive load, allowing for skill development within the time frame of a short experiment [65,66]. The task has previously been used in research where it was used to demonstrate that spaced practice in video games improved in-game performance consistently [52]. Performance in the game is tracked by (a) high score: their longest time spent playing without colliding with an obstacle and (b) the average duration: their average time between collisions, omitting the last round's time due to players being cut off by the time limit.

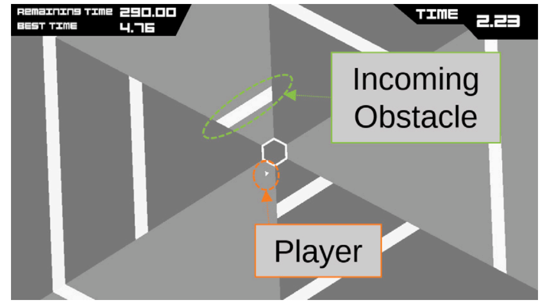


Fig. 1. A screenshot of the *Super Hexagon* clone used within the study.

Our version of the game included additional logging features over the original, but only implemented one level, based on the obstacles found in the commercial game and approximating the pacing and difficulty of the commercial game's first level. The order and presentation of the obstacles were fixed, providing stronger internal validity over using the commercial game. This clone was developed using the Unity game engine and its source code is available on GitHub.[1]

Our research agenda involved investigating a common motor learning theory in a digital context, and so we needed to select a game which featured a perceptual-motor skill to learn, like in a physical sport, but with digital aspects that made it different from any other perceptual-motor skill studied previously by sports psychology researchers. Super Hexagon met these needs in several ways.

First, it allowed us to present participants with the opportunity to learn a novel perceptual-motor skill unlike any they might find in the context of sports. This skill involved translating key presses that did not perfectly map to the on-screen action. For example, pressing the left arrow key moved the player on a clockwise arc about a central point, representing a more complex mapping than simply moving left on the screen. This is an additional translation step that is not needed in physical contexts, where a learner can often directly move their limbs to match a model [13], introducing some stimulus–response incompatibility to the learning environment [20].

Second, it allowed us the ability to present players with identical challenges for every trial, or to manipulate the trials to introduce variability in the attempts. This was leveraged in Study 2 to create videos to observe featuring random obstacles. This allowed us to explore whether differing conditions during observation would affect the transfer of knowledge, as it theoretically should [21].

Third, while the game features observable strategies – such as positioning near lane edges to minimize travel distance between safe zones – successful performance depends on developing procedural knowledge beyond simply knowing what to do. Players must learn the mapping between button presses and on-screen movement, and must practice parsing obstacles in real-time to identify safe routes. This reflects a key distinction in motor learning: declarative knowledge (knowing the strategy) does not automatically translate to procedural knowledge (executing it effectively) [67,68]. Observational learning is particularly

[1] https://github.com/colbyj/SuperHexagonClone

valuable in this context because, unlike verbal instruction, which primarily conveys declarative information, watching gameplay provides procedural knowledge such as timing, movement coordination, and spatial positioning strategies [13,15].

Finally, a simple game featuring only one skill to learn provided an experimental design with strong internal validity, while still maintaining external validity due to the clone being based on a successful commercial game. While more complex games could provide additional insights (as discussed in Section 5.4), Super Hexagon's simple design allowed us to design experiments with strong internal validity.

3.2. Questionnaires

3.2.1. Gaming expertise

We asked two questions to assess our participants' gaming experience: "Are you experienced at playing video games?" and "Are you a gamer?". The participants answered on a 5-point Likert Scale (1 = "not at all", 5 = "extremely"). The questions had a high internal consistency with a Cronbach's Alpha of .94 in Study 1 and .90 in Study 2.

We also asked participants if they had prior experience with Super Hexagon. In both studies, we asked, "Do you have previous experience with Super Hexagon?" ("Yes" or "No"). In Study 2, we added an additional question, "How familiar are you with the game 'Super Hexagon' on the following scale?" (a slider from 1 to 100).

3.2.2. Attentional control scale

The second questionnaire was the Attentional Control Scale (ACS) [69]. People with better attention and task-specific concentration were expected to outperform others with this task. The 20-item self-report questionnaire measured two dimensions: the ability to focus and the ability to shift attention, with responses on a 4-point Likert scale (1 = "almost", 4 = "always"). Participants were asked to answer questions like: "It's very hard for me to concentrate on a difficult task when there are noises around" and "I can quickly switch from one task to another". The ACS had a high internal consistency, with a Cronbach's alpha of .83 in Study 1 and .90 in Study 2.

3.2.3. Sport orientation questionnaire

Participants also completed the Sport Orientation Questionnaire (SOQ) [70]. This was included since competitive participants may exert more effort in the task. The 25-item self-report measurement featured three subcategories: competitiveness, win and goal orientation. An example question for the category competitiveness is "I am a competitive person". For the category win orientation "I have the most fun when I win". Lastly, an example question for the category goal orientation is "I set goals for myself when I compete" [70]. Participants could answer on a 5-point scale (1 = "strongly disagree", 5 = "strongly agree"). The different subscales had a high internal consistency in our studies with Cronbach's alpha coefficients of .86 (Study 1) and .89 (Study 2) for goal orientation, .86 (Study 1) and .90 (Study 2) for win orientation, and .94 (Study 1) and .90 (Study 2) for competitiveness. The SOQ also has a sensible reliability, with a test-retest reliability for each item ranging from .39 to .76 [70].

3.2.4. Mini player experience inventory

After the participants played the game, participants answered the Mini Player Experience Inventory (MiniPXI) [71]. This questionnaire has 11 items with a single item for the 11 constructs of the original PXI. An example of questions that were included in the MiniPXI is "I liked the look and feel of the game" or "the game was not too easy and not too hard to play". The MiniPXI had a single-item reliability average of .68, and the validity of 9 items out of 11 could be confirmed [71].

3.2.5. Subjective improvement

After playing the game, we asked participants questions about their own perception of their improvement in the game. In Study 1, we asked participants a single question relating to their subjective sense of their improvement: "Why do you feel your skills have (or have not) improved?".

In Study 2, we asked participants questions relating to improvement that differed depending on whether they watched a video or not. If they were a player (they did not watch a video), then they were asked two questions:

- "Do you think your skill and performance with this game improved over the play session?" (1 = "Much worse", 5 = "Much better")
- "What factors might have led to changes in performance over the play session?"

If they were an observer (and so they watched one of the two videos), they were asked five questions:

- "Do you think your skill and performance with this game improved from the first to the last session?" (1 = "Much worse", 5 = "Much better")
- "Did watching the gameplay video help your performance?" (a slider from 1-100)
- "Why do you think that watching the video did or did not help your performance?"
- "What other factors might have led to changes in performance between the first and last session?"

3.3. Procedure

3.3.1. Study 1

Participants participated in pairs, with one participant being randomly assigned the role of "player" and the other participant being assigned the "observer" role. Both participants joined the experimenter in the lab and sat side by side at a table with two PCs. The player always sat to the left of the observer. Participants had their backs to the experimenter in the lab and the experimenter was present throughout the experiment.

The overall procedure of Study 1 is outlined in Fig. 2. After providing consent, participants responded to the questionnaires via Qualtrics.[2] The first part of the questionnaire included questions on gaming experience, the Attention Control Scale (ACS), and the Sport Orientation Questionnaire (SOQ). After the initial questionnaires, both participants had to play the game for five minutes. This represented their baseline performance. Afterwards, the participants either had two five-minute practice sessions (as the "player") or were able to watch the other person play for both sessions (as the "observer"). The sessions were separated by one-minute breaks, which were included because incorporating breaks helps skill development compared to practicing continuously, ensuring that the players improve their skills while avoiding potential concerns around fatigue [51,52,72]. After the three practice or observation sessions, the participants played the post-session. After the post-session, participants then completed the MiniPXI questionnaire as well as a final question asking about subjective improvement.

During gameplay, participants were instructed to refrain from speaking to each other, especially about the game. This was an intentional methodological choice, made with the intent to isolate the effects of observational learning from verbal instruction or coaching, which is similar to how motor learning researchers have conducted experiments on observational learning [13]. Additionally, allowing participants to communicate at this time may have diverted some of the

[2] https://www.qualtrics.com

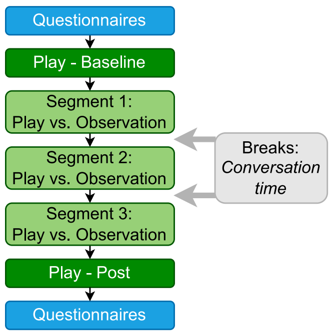


Fig. 2. The procedure of Study 1.

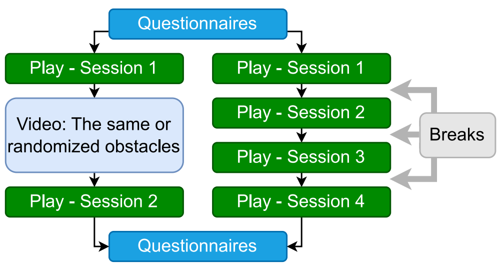


Fig. 3. The procedure of Study 2. The left path describes the procedure for participants who were assigned to watch a video; the right describes the procedure for participants who were assigned to play only.

players' attention to verbal processing, which could have affected performance [66,73]. Similarly, past work in the domain of motor learning has found that attempts to apply task-relevant verbal knowledge can be detrimental to performance in the short term, particularly compared to learning a skill implicitly (i.e., via a demonstration) [68].

During the breaks, we instructed participants that they could do whatever they wanted, including talking. Any conversations that took place during the breaks were audio-recorded. By allowing free conversation during the breaks, we could observe whether participants naturally focused on improving at the game, for example, by spontaneously engaging in collaborative learning or coaching. While this could also affect the player's performance, it is an ecologically valid aspect of many social gaming contexts.

3.3.2. Study 2

The experiment was presented via a custom website implemented by leveraging an online web framework designed for the creation of online experiments [74]. The procedure is described by Fig. 3. Upon giving consent, participants were automatically assigned to be either a player, or one of two types of observers. Participants completed the experiment individually, by participating online from their own computers. Next, participants would complete the first set of questionnaires, consisting of demographics, gaming experience, the ACS, and the SOQ. All participants then played the first session of the game. Next, participants assigned to be players continued playing the game after a one-minute break while the observers switch to watching a video (one of two variations). After the video, observers switched back to the game to play their final session. After playing the game, participants completed the final set of questionnaires, which included the MiniPXI and a questionnaire about subjective improvement.

The video featured 10 min of pre-recorded gameplay without commentary showing either a level that was identical to what participants were playing, or a level with entirely random sequences of obstacles where no attempt was the same. The recorded player was an intermediate player of Super Hexagon whose average life time for an attempt was about 33 s when attempting the random levels and about 39 s when attempting the level with a fixed sequence of obstacles. The use of a pre-recorded video instead of a live viewing was intended to model the ecologically valid scenario of a player watching an in-game replay or a video without commentary. This design also allowed us to fully isolate the effects of observational learning from the possible confounding factor of verbal instructions.

3.4. Participants

3.4.1. Study 1

A total of 26 individuals in 13 pairs participated in Study 1. Of these, we excluded two from our analyses due to prior Super Hexagon experience, and one more from our analysis due to being an outlier in terms of age. This left 23 participants, aged 18 to 25 ($M = 20.1$, $SD = 2.12$), who participated in Study 1. Of these, 19 identified as female, three as male and one as non-binary/third gender. The majority of participants identified as "not at all" gamers (n=12), while others reported being "slightly" (n=3), "moderately" (n=4), "quite a bit" (n=1), or "extremely" (n=3) gamers. In terms of gaming experience, fewer participants claimed to be "not at all" experienced (n=6). The remaining participants reported varying levels of experience: "slightly" (n=6), "moderately" (n=4), "quite a bit" (n=3), and "extremely" (n=4). Ten participants were Observers and 13 were Players. All participants had normal or corrected-to-corrected vision.

Participants were recruited through convenience sampling, with the majority gathered through SONA, a website used by the University of Twente to facilitate the recruitment of first-year psychology students. Participants who were enrolled as students received course credit for completing the study. A small number of additional participants were uncompensated friends of one of the authors. The study was approved by the Ethics Committee of the University of Twente and participants provided informed consent before participation.

3.4.2. Study 2

A total of 93 individuals participated in Study 2. Of these, eleven were excluded from consideration due to not making any inputs on over 63% of their trials within the game (our cut-off was 50%), and five were excluded due to skipping over the video. An additional seven were excluded due to having prior experience playing Super Hexagon, and one was excluded based on being more than 3 standard deviations older than the mean. The remaining 69 participants were aged 21 to 62 ($M = 35.5$, $SD = 9.83$). 43 participants identified as male, 25 identified as female, and one participant self-described themselves as "non-binary (F)". Participants in Study 2 tended to identify as a gamer, with only some saying they were "not at all" gamers (n=5), while others reported being "slightly" (n=13), "moderately" (n=17), "quite a bit" (n=16), or "extremely" (n=18) gamers. In terms of gaming experience, the responses were similar, with only some saying they were "not at all" experienced (n=8) and the rest saying "slightly" (n=15), "moderately" (n=18), "quite a bit" (n=19), and "extremely" (n=9). We had 25 participants assigned to be Players, 24 assigned to be Randomized Level Observers, and 20 assigned to be Same Level Observers.

Participants were recruited from Prolific,[3] an online platform that connects researchers with participants. Participant data from Prolific has been reported to be of higher quality than from Amazon's Mechanical Turk, or a sample of undergraduate students [75]. The study was approved by the Ethics Committee of the University of <Removed for blind review> and participants provided informed consent before participation.

[3] https://www.prolific.com

3.5. Data analyses

3.5.1. Quantitative analyses

Unless stated otherwise, the same quantitative analysis approach was used for both studies.

Initial Performance. To determine whether there were differences between the groups (player vs. observer) in the first session's performance (average life and maximum life time), we used separate independent samples t-tests (one test per performance measure) for Study 1, and an ANOVA in Study 2.

Individual Differences. To ensure that our participant groups were comparable, we analyzed the questionnaires for differences between the groups. This was done using separate independent samples t-tests for each questionnaire's subscale.

Subjective Experience. To compare differences in subjective experience of the game, we analyzed each question of the MiniPXI using separate independent samples t-tests in Study 1, and using an ANOVA in Study 2.

Improvements Over Time. To explore the change over time in our in-game performance measures we looked at the groups in isolation and used separate paired sample t-tests to compare performance (average life time and max life time) between the second session and the first session, as well as the last session and the first session, with the hypothesis that the later sessions would have a higher performance than the first session.

Differences Between Groups. To probe the effect of observation, we assessed the difference in performance between the second session and the first session between the groups. In Study 1, we used a single independent samples t-test to compare between observers and players. In Study 2, we used three separate independent samples t-tests to perform comparisons between each observer group and the players, and between the two observer groups, and did this for both performance measures.

Jamovi [76] was used to complete all quantitative analyses. Alpha was set at .05.

3.5.2. Qualitative analyses

Study 1. In order to supplement the quantitative analysis and contextualize the analysis, two separate inductive thematic analyses based on the procedure outlined by Braun and Clarke [77] were conducted. The first one was on what participants were discussing amongst themselves during their breaks and the second was on a final question we asked participants ("Why do you feel your skills have (or have not) improved?"). The thematic analysis of the conversations in the breaks was completed by the second and third author and the first author completed the thematic analysis of the final question. All codes were cross-checked by all authors.

Study 2. In Study 2, we asked all observers: "Why do you think that watching the video did or did not help your performance?" and all participants: "What (other) factors might have led to changes in performance over the play session?". The methods used to analyze these responses were the same as in Study 1 — an inductive thematic analysis completed by the first author which was cross-checked by all other authors.

4. Results

4.1. Quantitative results

4.1.1. Initial performance

In Study 1, there was a significant difference in performance on the first session between Players and Observers, for average life time ($t_{21} = -2.25$, $p = .035$ (95% CI: −14.0, −0.56)) and for maximum life time ($t_{21} = -2.19$, $p = .040$ (95% CI: −24.8, -.066)). Players started out with higher initial performance than the Observers.

In Study 2, there was no main effect of group on the performance on the first session, for average life time ($F_{2,66} = 0.24$, $p = .790$) or maximum life time ($F_{2,66} = 1.63$, $p = .204$).

In order to be independent of the precise performance at the start of the experiment difference values were calculated reflecting performance changes over time. Specifically, the difference between the first and last session as well as the difference between the 1st and the 2nd play session was calculated. See Table 1 for details.

4.1.2. Individual differences

In Study 1, there were only minor differences between participants for our measures of individual differences. Specifically, only the competitiveness subscale of the SOQ was significantly different between the two roles. The players scored higher on competitiveness ($M = 3.43$, $SD = 0.74$) than the observers ($M = 2.64$, $SD = 1.05$), ($t_{25} = -2.23$, $p = .037$). However, there were no significant correlation between any of the questionnaires (i.e., ACS or SOQ) or the demographics and any performance variable (r's between -.2 to .3, with all p's >.05).

In Study 2, there were no differences between participants for our measures of individual differences (all $p \geq .280$).

4.1.3. Subjective experience

In Study 1, for the MiniPXI, there was only one measure where the players and observers significantly differed. The players rated their curiosity as higher than the observers. See Table 2.

In Study 2, there was only one MiniPXI measure with a main effect of group — Progress Feedback. Pairwise comparisons showed that the Same Level Observers rated the game as providing clearer feedback than either the Players ($p = .013$) or the Random Level Observers ($p = .044$). The Random Level Observers and Players rated the feedback similarly ($p = .620$). See Table 3.

4.1.4. Performance over time (H1)

Our results show that all groups improved their performance over the duration of the study, for both studies. Their performance in the last session was significantly improved over their performance in the first session, for average life time and maximum life time (see Table 4). See Fig. 4 to see descriptive changes in performance over time between the first and last sessions for both studies. This provides support for H1.

4.1.5. Observational learning (H2)

To evaluate the effects of observational learning, we look at performance improvements between the second session and the first session and compare between the groups at this point in time. We find that in Study 1, the Observers significantly improved their performance between the second session and the first session, but the players did not, for both average life time and maximum life time. In Study 2, all groups improved their performance between the second session and the first session, for both performance measures (see Table 4). See Fig. 4 to see descriptive changes in performance over time between the first and second sessions for both studies. This provides partial support for H2.

Comparing between the groups, in Study 1, we found that the Observers significantly improved their performance over the Players. In Study 2, only the Same Level Observers improved their performance over the Players (see Table 5). This provides partial support for H2.

4.1.6. Final performance (H3)

Examining the differences between the groups in performance gains from the first to last session in Study 1, we see that the Players improved more in the end than the Observers. In Study 2, however, we see no differences between the groups in terms of performance gains between the first and last session; all groups improved a similar amount. For a visual representation of this see Fig. 4. This provides partial support for H3.

Table 1

Descriptive statistics of first (baseline) session, as well as the difference in sections between first and the second session and between the first and last session, for both studies. Note that because observers only played two sessions the change to the second session is equal to the change to the last session.

	Variable	Group	N	First session				Second-first				Last-first			
				Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Study 1	Average Life Time	*Overall*	23	16.19	8.36	6.10	33.4	5.76	7.64	−10.54	19.4	13.93	8.46	2.06	37.2
		Observer	10	12.08	7.32	6.10	28.9	9.98	4.35	5.01	19.0	9.98	4.35	5.01	19.0
		Player	13	19.35	7.94	8.07	33.4	2.51	8.16	−10.54	19.4	16.97	9.69	2.06	37.2
	Max Life Time	*Overall*	23	34.46	14.93	14.74	67.4	7.88	13.94	−15.07	40.4	16.08	14.41	0.38	43.6
		Observer	10	27.27	9.89	14.74	46.9	12.59	14.17	0.38	40.4	12.59	14.17	0.38	40.4
		Player	13	39.98	16.09	20.63	67.4	4.26	13.16	−15.07	34.8	18.76	14.56	2.62	43.6
Study 2	Average Life Time	*Overall*	70	8.26	4.21	3.22	23.0	3.78	3.21	−0.80	14.4	3.94	3.52	−2.60	14.4
		Obs. (Random)	24	8.11	4.66	3.55	23.0	3.67	2.58	0.36	12.1	3.67	2.58	0.35	12.1
		Obs. (Same)	21	8.66	4.17	3.22	19.7	4.88	3.59	−0.29	14.4	4.88	3.59	−0.29	14.4
		Player	25	8.07	3.92	3.35	15.8	2.96	3.28	−0.80	11.2	3.41	4.16	−2.60	12.1
	Max Life Time	*Overall*	70	16.32	7.75	5.23	41.2	4.08	5.40	−12.47	18.6	5.15	6.66	−12.47	25.8
		Obs. (Random)	24	14.70	6.86	5.23	35.8	5.12	4.33	0.01	15.5	5.12	4.33	0.01	15.5
		Obs. (Same)	21	18.37	8.91	5.25	41.2	3.83	6.03	−12.47	16.4	3.83	6.03	−12.47	16.4
		Player	25	16.15	7.41	5.23	28.7	3.28	5.80	−4.08	18.6	6.30	8.74	−11.41	25.8

Table 2

Descriptive statistics and statistical results from the independent sample t-tests for the MiniPXI measures in Study 1.

PXI variable	t_{21}	p	Observer		Player	
			Mean	SD	Mean	SD
Audiovisual Appeal	−1.55	.136	3.90	1.79	4.92	1.38
Challenge	−1.29	.211	4.80	1.40	5.54	1.33
Ease of Control	−0.13	.894	6.50	0.53	6.54	0.78
Clarity of Goals	0.03	.978	6.70	0.68	6.69	0.63
Progress Feedback	−0.33	.748	4.20	1.93	4.46	1.90
Autonomy	−0.82	.423	4.60	2.22	5.31	1.93
Curiosity	**−2.34**	**.029**	**4.70**	**2.00**	**6.08**	**0.64**
Immersion	0.19	.849	6.00	0.94	5.92	0.95
Mastery	−0.91	.375	3.90	1.91	4.62	1.85
Meaning	−0.93	.363	3.20	1.69	3.85	1.63
Enjoyment	−1.42	.170	4.60	1.96	5.46	0.88

Table 3

Descriptive statistics and statistical results for the ANOVAs for the PXI questionnaire in Study 2.

PXI variable	$F_{2,66}$	p	Observer (Random)		Observer (Same)		Player	
			Mean	SD	Mean	SD	Mean	SD
Audiovisual Appeal	1.45	.242	4.83	1.66	5.45	1.47	4.60	1.89
Challenge	0.49	.615	4.54	1.74	5.00	1.38	4.88	1.67
Ease of Control	0.41	.669	5.71	1.65	5.90	1.41	5.44	2.00
Clarity of Goals	0.69	.505	5.92	1.38	6.15	0.81	5.68	1.60
Progress Feedback	**3.55**	**.034**	**4.92**	**1.72**	**5.95**	**1.05**	**4.68**	**1.97**
Autonomy	1.55	.220	5.67	1.20	5.40	1.67	4.88	1.83
Curiosity	2.82	.067	5.71	1.20	5.80	1.20	4.84	1.99
Immersion	1.45	.243	6.25	0.79	6.40	0.68	5.96	1.10
Mastery	0.24	.786	4.13	1.83	4.55	2.21	4.24	2.17
Meaning	1.29	.281	4.42	1.98	4.85	2.11	3.88	2.01
Enjoyment	0.47	.625	5.00	1.72	5.45	1.40	5.04	1.81

4.1.7. Sequence learning (H4)

In Study 2, only the Same Level Observers improved their performance over the Players. See Table 5. This provides support for H4.

4.2. Qualitative results

4.2.1. Break time discussions (study 1)

The audio recordings of the conversations during the breaks were analyzed. The content of the breaks was divided into three separate categories: unrelated to the game (e.g., “Can you give me my water?”), related to the game (e.g., “This game is hard!”) and game tactics (e.g., “You notice when it turns like this you are better off going this way”.). For an overview see Table 6.

The most theoretically intriguing category was game tactics. Discussions categorized as in-game tactics talked about the mechanics of the games and/or different tactics that could be used to perform better at the game. For example the following dialogue between two participants: “P19: It’s basically dodging or standing in one of these lines”. P20: “It’s so claustrophobic. I could get so, so little space”. P19: “Yeah, but I mean, the way, you know, if you are in the same space, if you just wanted between these lines that it never intersects them. Usually leaves one of these just fully open. So you can just stand there”.

Most pairs – 11 out of 13 – talked about several different topics and were classified within different categories over the two breaks. Only one pair was qualified as unrelated in both breaks. Both participants of this pair showed decreased performance from baseline to post-condition (with a performance decrease of 18.84 s and 12.08 s respectively). Another pair who talked about game tactics in both breaks improved their average and maximum time from baseline to post-condition (average increase of 8.82 s and 8.52 s, maximum increase of 18.99 s and 1.42 s respectively). Although the effect of conversational topics cannot be determined with the present data, the thought of strategy talk affecting performance is intriguing.

4.2.2. Self-reported skill improvements

In Study 1, we asked participants “Do you think your skill and performance with this game have improved from the first to last time you played today?”. All of our participants felt that they were much better or somewhat better (mean=4.38, SD=0.50, min=4, max=5). This was did not differ between the groups; both observers (mean=4.23, SD=0.44, min=4, max=5) and players (mean=4.54, SD=0.52, min=4, max=5) felt that they improved at the game, and there were no differences between the groups ($t_{24} = -1.63$, $p = .116$)

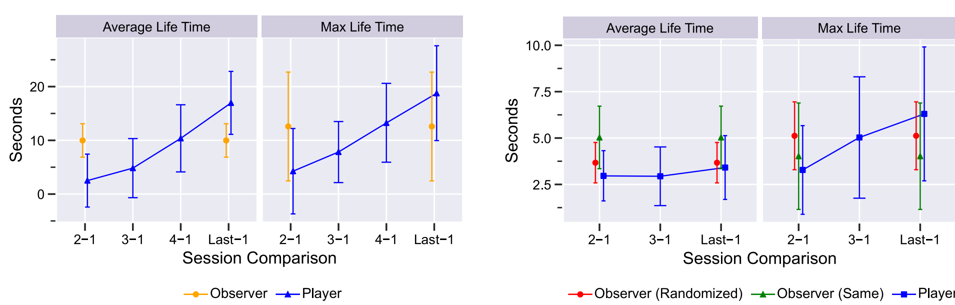
In Study 1, we also asked participants, “why do you feel your skills have (or have not) improved?” Some participants gave responses that cited evidence for why they got better at the game (N=8, 4 observers, 4 players), for example, “because I got a better score” (P19, player). Other participants provided one or more reasons for their improvement (N=18, 10 observers, 8 players), with the most common response relating to the benefits of observation (N=7, all observers), for example, “I observed the players tactics and tried applying them myself”. (P8, observer). The next most common type of response related to practice (N=6, 1 observer, 5 players), for example, “i found my own technique, got more used to the look and the way of playing” (P7, player). Apart from this, 3 participants (all players) mentioned memorization in some way (e.g., “I could remember in which order the white things come”, (P17, player)).

Table 4
Within-subjects results for Study 1 and Study 2. Note that for Observers, the comparison between the Last session and First session is the same as the comparisons between the Second session and First session.

	Session comparison	Group	df	Avg. life time		Max. life time	
				t	*p*	*t*	*p*
Study 1	Second - First (H2)	*Overall*	22	**3.62**	<.001	**2.71**	**.006**
		Observers	9	**7.26**	<.001	**2.81**	**.010**
		Players	12	1.11	.144	1.17	.133
	Last - First (H1)	*Overall*	22	**7.90**	<.001	**5.35**	<.001
		Observers	9	**7.26**	<.001	**2.81**	**.010**
		Players	12	**6.31**	<.001	**4.65**	<.001
Study 2	Second - First (H2)	*Overall*	69	**9.86**	<.001	**6.32**	<.001
		Observers (Random)	23	**6.97**	<.001	**5.80**	<.001
		Observers (Same)	19	**6.25**	<.001	**2.93**	**.004**
		Players	24	**4.52**	<.001	**2.83**	**.005**
	Last - First (H1)	*Overall*	69	**10.00**	<.001	**6.47**	<.001
		Observers (Random)	23	**6.97**	<.001	**5.80**	<.001
		Observers (Same)	19	**6.25**	<.001	**2.93**	<.001
		Players	24	**4.10**	<.001	**3.60**	<.001

Table 5
Between-subjects results for Study 1 and Study 2.

	Session comparison	Group comparison	df	Avg. life time		Max. life time	
				t	*p*	*t*	*p*
Study 1	Second - First (H2)	*Observers - Players*	21	**2.61**	**.016**	1.46	.160
	Last - First (H3)	*Observers - Players*	21	**−2.12**	**.046**	−1.02	.319
Study 2	Second - First (H2, H4)	*Observers (Random) - Players*	47	0.84	.406	1.25	.216
		Observers (Same) - Players	43	**2.02**	**.050**	0.41	.681
		Obs. (Random) - Obs. (Same)	42	−1.46	.152	0.70	.490
	Last - First (H3)	*Observers (Random) - Players*	47	0.26	.793	−0.60	.555
		Observers (Same) - Players	43	1.38	.175	−0.99	.329
		Obs. (Random) - Obs. (Same)	42	−1.46	.152	0.70	.490



(a) Study 1 (b) Study 2

Fig. 4. Plots depicting the change in performance over time. Positive numbers on the *y*-axis indicate performance improvements (and vice versa for negative values). For players, the 2nd session occurred only after a short break directly after the first session. For the observers, the 2nd session took place only after the opportunity to observe three live sessions by another player (Study 1) or two recorded sessions (Study 2). For observers, their last session was also their 2nd session, so the values for their two points are identical. Error bars are 95% confidence intervals.

Table 6
The categorization of the conversations of each of the pairs for both of the breaks.

	Category	Number of pairs
First Break	Unrelated to game	3
	Related to game	7
	Tactics	6
Second Break	Unrelated to game	8
	Related to game	7
	Tactics	2

In Study 2 we asked participants "Do you think your skill and performance with this game improved over the play session?". On average, our participants felt that they were "somewhat better" (mean=3.87, SD=0.97, min=1, max=5). This did not differ between the groups ($F_{2,66}$ = 0.894, p = .414), with Players (mean=4.08, SD=0.83, min=2, max=5), Same Level Observers (mean=3.75, SD=0.97, min=2, max=5), and Random Level Observers (mean=3.76, SD=1.09, min=1, max=5) all reporting similar perceptions about their improvement within the game.

In Study 2, we also asked several questions relating to potential reasons for performance improvements. We asked both groups of observers "Did watching the gameplay video help your performance?", with the response being a score from 1 to 100. On average, participants thought that the video did somewhat help performance (mean=63.1, SD=34.4, min=1, max=100), with no difference between the two observation groups (t_{42} = 0.601, p = .551). For the two qualitative, open-ended

Table 7
Summary of the results of the inductive thematic analysis for Study 2.

Theme	Sub-theme	N	Example response
Video Helpful (N=31)	Strategy	11	*"It helped it because I figured the best and smoothest ways to make my movements round the hexagon."* -P98
	Understanding	10	*"It really exposed me to how the game works."* -P99
	Inspiring	6	*"I became confident that if somebody did it I too can do it."* -P82
	Showed Patterns	3	*" it also gave me a better understanding of how I was to navigate through the maze."* -P94
Practice		18	*"Playing the game again and again has helped me familiarize myself with the game and improved my performance."* -P79
Emotional Control		7	*"I think the key at performing well is to stay calm and not give up. You need to believe in yourself."* -P26
Memorization		7	*"I understood the patterns of the hexagon better."* -P87
Video Not Helpful		6	*"With this game particularly I found it was a little too simple of a concept to learn anything from watching somebody play it"* -P21
Comments About Game		5	*"I had a hard time playing the game because of the slowness of my keyboard."* -P28
Break Was Helpful		3	*"The chance to have a rest and reflect on the game, taking time out from a task allows you to approach it with fresh ideas."* -P18

questions relating to reasons for performance improvement, a summary of the thematic analysis of the responses is shown in Table 7. In general, the responses identified a variety of reasons why the videos helped them learn the game, including revealing the game's strategy, allowing them to better understand how the game worked, showing them the specific patterns of the obstacles they were encountering, and also inspiring them to play better. Aside from the videos, practice was given as the main reason for improvement within the game.

5. Discussion

5.1. Summary of results

This study aimed to assess whether observational learning can be applied as a tool to help players improve at the games they play. Our results indicate that there *are* performance benefits to watching others play.

First, we confirmed that all players improved at the game over time, regardless of whether they observed or played, and regardless of the type of observation (H1).

Second, we confirmed that observational learning occurred in Study 1 and found partial support for observational learning in Study 2 (H2). in Study 1, observers significantly improved their performance between their first and second session while players did not. Additionally, comparing between each group's second play session, we found that observers outperformed players in Study 1. In Study 2, we found that the observers who viewed the same level as they played on improved their performance over the players.

Third, we confirmed that time spent playing the game was more effective for improving at the game compared to observation in Study 1 but not Study 2 (H3). In Study 2, we found that all groups performed similarly to one another at the final play session.

Fourth, we confirmed that watching a video with the same sequence of obstacles was more effective for learning than a video with a randomized sequence of obstacles (H4).

Players watching one another in the same room have the opportunity to interact and converse with one another. In Study 1, we observed that when given the opportunity to talk with one another for one minute, conversations quite often turned towards the game itself. Of 13 pairs, all but one discussed the game in some way, for example, about tactics relating to how to play the game more effectively.

Participants in both studies subjectively felt that they improved at the game. In Study 1, when asked generally whether they thought they were better at the game at the end and why, seven of the 13 observers made comments relating to feeling as though they learned something through observation. In Study 2, observers gave a variety of reasons why observing another player via a video was helpful, with most observers agreeing that the video was helpful.

5.2. Theoretical implications

Our studies provide new insights into the effect of observational learning on perceptual motor skills, particularly within the gaming context. In line with existing research on observational learning and skill development across various domains [30,31,47,53], the findings of these studies suggest that observational learning can benefit the development of skills in gaming.

The results of our studies suggest that a combined approach involving both active practice and observational learning might be more beneficial for game skill enhancement than active practice or observation on their own — similar to physical contexts [47,78]. Some players could intuitively believe that actively playing the game is always a better strategy, but we clearly observed in Study 1 that participants who played without observing between sessions did not improve at the game between sessions 1 and 2, while participants who observed between these sessions improved substantially (H2). This suggests that observational learning can provide immediate performance benefits for players.

Study 1 revealed that players who had more practice sessions significantly outperformed their counterparts in average time. This was not the case when the practice sessions were not included, underscoring the importance of the extra practice sessions.

More uniquely, our results also reveal important differences in how observational learning operates in digital games compared to a traditional motor learning context. In the physical realm, observation succeeds in part due to learners being able to imitate actions directly [79]. In the digital realm, actions are carried out indirectly through input devices such as keyboards, mice, or gamepads. On-screen actions must be translated into specific button presses or mouse movements. In our studies, participants may have been able to observe the other player's avatar rotate on the screen, but could not see directly which buttons were being pressed. Despite the need to translate on-screen visuals to button presses, we still observed performance improvements (H2).

If direct imitation was not the mechanism that allowed learners to improve at the game, then other explanations that apply in the physical realm may explain why observation was effective. In Study 2, we explored whether sequence learning may have been a factor, as it is in the physical realm [15,16]. We found that observing the specific sequence that matched the sequence they were practicing was crucial for successful transfer (H4). Observers who watched randomized sequences of obstacles received significantly less benefit from observation.

These findings demonstrate that even if observational learning occurs in both physical sports and digital games, that the underlying mechanisms for *why* learning occurs differs.

5.3. Practical implications

Improving player skill development has become a major motivator in the context of the growing video game industry, which is always looking for new and exciting methods to engage and inspire players. Even though streaming has been very popular among gamers, on platforms like Twitch, its potential to help improve gamers' skills has been underexplored. While our work primarily aims to address the current gap in empirical research studying observational learning in games, our results also have clear implications for game designers seeking to explicitly design observation-related features to support player skill development through observational learning.

First, our findings as a whole suggest that game designers should incorporate as many opportunities as possible to view what other players are doing or have done. Considering the finding that time spent playing the game is still an important predictor of success in the game (H3), this suggests that it is important that opportunities to watch should be interleaved with opportunities to play the game — a strategy that many games already apply (for example, being able to spectate other players while waiting for a new round to start in *Counter-Strike* [80]).

Second, our finding that observation provides immediate performance benefits (H2) suggests that observation could be particularly valuable in certain scenarios. In particular, the early experiences in a game are where players are most likely to abruptly quit playing [81] and so could most benefit from the benefits of observation. While many games already incorporate observation features (e.g., spectator modes in competitive games like League of Legends, or ghost replay systems in racing games), these features are not commonly introduced or explained early in the learning process. One notable exception is fighting games such as *Tekken 8* [82] or *Street Fighter 6* [83], both of which heavily incorporate visual demonstrations of specific moves in the onboarding process. Our results suggest such features could be integrated into tutorial and onboarding systems to accelerate early skill development.

Our findings for H2 also suggest that observation could be leveraged as a game difficulty balancing mechanism. Past research highlights how games are boring when they are too easy, but frustrating when they are too hard [84]. Some systems attempt to achieve balance by modifying the challenge within the game [84]; however, an alternative approach could involve maintaining the same challenge but providing scaffolding to the player [5]. Struggling players could be given opportunities to observe other players to help them become better at the game and therefore better matched to its challenges. Similarly, but from the perspective of level design, if certain sections of a game are known to be particularly challenging, then players could potentially observe a model to learn how to pass the challenge. This approach could provide psychological benefits by allowing learning without needing to experience repeated failure [85], a common reason why players abandon games [10]. Observational learning offers a feasible and less taxing path to skill advancement, which may lessen player frustration and subsequently motivate them to play for longer the next time they pick up a game to play themselves, due to preserving the motivational benefits that come from overcoming challenges [9].

Third, our finding that sequence-specific observation is the most beneficial for learning (H4) has direct design implications: opportunities to observe should be closely matched to the challenges that the player will face. For example, rather than showing a random live stream of someone playing the same game, the game could show the player recordings of other players attempting the same challenge under the same circumstances.

Finally, our qualitative findings from Study 1 highlight the social aspects of observational learning — players spontaneously engaged in collaborative learning, discussing topics such as game strategies or engaging in explicit coaching. That this collaborative learning occurred naturally suggests that there are benefits to observation beyond the immediate performance benefits; it can serve as a catalyst for verbal discussion about the game.

Game designers could deliberately introduce opportunities for discussion and collaborative learning in response to observation. This has been incorporated in basic ways for games which can largely be played without other players concurrently in the game; consider how players of *Dark Souls* [86] or *Elden Ring* [87] can leave messages within the game world to one another, helping their fellow players with certain aspects of the game, and how this interacts with "blood stains". These are recorded ghostly characters within the game that demonstrate the last seconds before a player's death, shown to help players avoid the same fate as those who played previously. Similarly, racing games allow players to observe how other players traversed through a race track by placing a "ghost" of the other player on the track. This serves as a model that the player can follow. Our findings suggest that these approaches will be effective because they provide observation that is well-matched to the upcoming challenges that the player will attempt (or is presently attempting).

5.4. Limitations and future work

Several limitations must be acknowledged. Firstly, the decision to limit or eliminate verbal information during observation affects the ecological validity of the work by creating experimental conditions that differ from typical contexts where observational learning is applied. These include Twitch streams, which include commentary from the observed player as well as chat amongst all observers, and couch co-op scenarios, where players and observers can freely communicate. This was an intentional methodological approach to mirror the way that prior motor learning research separates visual demonstrations from verbal instructions [13]. However, we note that this design does maintain ecological validity by reflecting some gaming scenarios where silent observation is the norm. For example, watching replays or analyzing speedrun footage in an attempt to optimize a route. The discussions about the game that emerged during the breaks in Study 1, while potentially introducing a confound, also represent an ecologically valid aspect of social gaming contexts, and Study 2 was designed to eliminate this potential confound entirely.

Second, Study 1's small sample size (n=23) limits statistical generalizability. However, we observed very large effect sizes for the key observational learning effects (Cohen's d = 2.30 for average life time improvement, d = 0.89 for maximum life time improvement from Session 1 to Session 2 for observers), indicating robust performance changes despite the small sample. Study 2's larger sample (n=69) and online methodology provided broader demographic diversity and replication of key findings, strengthening confidence in the results.

Another limitation is that there are several variables that affect the efficacy of observational learning that we did not control for. In particular, our participants in Study 1 were mostly students of similar age, and past work has found that observational learning is positively affected by similarity between the learner and model [47]. Given that with the design of our study, our models were also our participants, we also did not control for the competence of the model, which may affect the effectiveness of the observation [13], although past work has found that novices and experts can both be effective models [44]. We addressed these concerns in Study 2, where we explored a more diverse population via an online study and where the competence of the model was controlled by using a pre-recorded video.

Future work could explore how different types of models affect observation, not only in terms of similarity to the learner and competence of the model, but also in terms of modality of the model. Our model was live and in-person, but it is very common for novices to turn to pre-recorded videos on YouTube or live-streamed performances on Twitch. These different modalities afford different levels of social interaction than an in-person model. For example, a learner can leave comments on YouTube videos to clarify details of the demonstration and elicit help from other viewers, and on Twitch, those comments and responses can be live, and the model themselves may also respond to comments regarding their demonstration.

Further limitations and future work relate to game selection. As explained in Section 3.1, Super Hexagon allowed us to study perceptual-motor skill learning while maintaining strong experimental control. The game features the abstraction layer characteristic of digital games (keyboard inputs mapped to circular motion) while presenting identical challenges across attempts. This simple game with a single skill to master, however, limits generalizability. Games with multiple skills to learn might afford players more opportunities to acquire knowledge from visual demonstrations, and the specific skill that players were learning may not have been the best candidate for observational learning.

Consider, for example, how effective observational learning would be if a new player simply needed to follow a specific sequence of steps to succeed. Games or game genres which feature easily reproducible strategies for success (e.g., puzzle games like *Baba Is You* [88]) are likely better suited to learning through observation. Super Hexagon was chosen particularly because it depends on motor skill development as well as sequence learning; a game that focuses solely on perceptual-motor skill development may not be one that can be learned as effectively through observation.

Additionally, it is possible that in Super Hexagon, because of the need to translate on-screen rotations to specific button presses, players could not as easily mimic the demonstrations — players might have known exactly what they needed to do but still not be able to do it. This translation may have prevented the video from aiding motor skill development, and this could, in part, explain why sequence learning was a significant factor in Study 2. If the video was less effective at allowing players to learn the specific perceptual-motor skills required to succeed, then the sequence of the obstacles matching the actual challenge would be essential to ensuring the observation is providing the player with useful information to help them perform well at the game. Future work should explore this more explicitly by investigating the role of stimulus–response compatibility in observational learning.

Furthermore, sports research showed that the complexity of the task can influence the effectiveness of observational learning [89]. Therefore, our results may not generalize to complex games with a variety of skills to learn or featuring different kinds of challenges (e.g., see [90] for an overview of different challenges found within games).

Finally, we believe that in the context of digital gaming, attention should be given to the experience of being observed. The theory of social facilitation suggests that participants could perform a simple task better when watched by others [91] and it is possible that being observed increases the pressure felt by the player, which could affect their performance [92] and enjoyment of the game. This notion is supported by recent research [93] that found that if players were observed, especially by someone who was introduced as a researcher, they would perform better at several video games. In Study 1, our lab setting therefore may have increased pressure compared to playing at home with friends or family, and this pressure may have differed whether the participant was the observer or the player in the study. Outside of our study, the pressure from observation might also be different depending on whether the performance is live or pre-recorded, whether live feedback from in-person viewers or viewers of a live stream is present, or whether the observation is from other players within an online multiplayer game. Because digital gaming is a leisure activity, it is important that the experience be enjoyable for everyone involved, and therefore, future research examining different modes of presenting models should consider the effects that observation has on the model.

6. Conclusion

We set out to explore the potential of observational learning as a tool to enhance players' performance in digital games. We explored this within a clone of the commercial game, *Super Hexagon* and two studies. One using a study involving pairs of participants — one participant taking the role of player and the other taking the role of observer, and another involving participants watching a video.

Our findings provide controlled experimental evidence that the differences found in digital games compared to physical sports are not enough to prevent observational learning from being effective. Observational learning in digital games has the potential to provide meaningful and measurable performance benefits under specific conditions. We empirically demonstrated that learning through observation is a viable method for acquiring skills in games that can accompany practice, particularly for novice players. Observing gameplay with intentionality – for example, observing gameplay that features challenges similar to the ones a player is trying to overcome – can enhance the learning process.

Social dynamics also played a role in the efficacy of learning through observation. In Study 1, opportunities for our participant pairs to interact with one another during breaks in gameplay led to discussions about various aspects of the game, including strategies for success — participants did make attempts to coach one another. In both studies, subjectively, all of our participants thought they got better at the game by the end of the study and many observers felt that a reason for their improvements in the game was some aspect of the observation.

Our studies demonstrate that observational learning can be a valuable tool for helping new players learn and improve at the games they play. While actively playing the game remains an important factor determining a player's success, the process of observing another player provides novices with significant benefits, such as opportunities to learn different strategies and help with overcoming a game's challenges. This work takes an important step towards understanding how observational learning can be applied and the potential implications within the context of digital gaming.

CRediT authorship contribution statement

Colby Johanson: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Hannah Wessels:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Maximilian A. Friehs:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Chat GPT 4o and Claude Sonnet as brainstorming aids and to refine the clarity of the written manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

https://osf.io/fxa9c/files.

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