

Action video game playing impacts occupational screening for high-stakes professionals

Received: 28 September 2025

Accepted: 28 April 2026

Cite this article as: Cochrane, A., Sibley, C., NeSmith, R. *et al.* Action video game playing impacts occupational screening for high-stakes professionals. *Commun Psychol* (2026). <https://doi.org/10.1038/s44271-026-00470-3>

Aaron Cochrane, Ciara Sibley, Rebecca NeSmith, C. Shawn Green & Daphne Bavelier

We are providing an unedited version of this manuscript to give early access to its findings. Before final publication, the manuscript will undergo further editing. Please note there may be errors present which affect the content, and all legal disclaimers apply.

If this paper is publishing under a Transparent Peer Review model then Peer Review reports will publish with the final article.

Action video game playing impacts occupational screening for high-stakes professionals

Aaron Cochrane¹, Ciara Sibley², Rebecca NeSmith³, C. Shawn Green⁴, Daphne Bavelier^{5,6}

¹Brown University, Providence, RI, USA

²US Naval Research Laboratory, Washington, DC, USA

³Naval Aerospace Medical Institute, Pensacola, FL, USA

⁴University of Wisconsin – Madison, Madison, WI, USA

⁵University of Geneva - Geneva – Switzerland, Geneva, GE, Switzerland

⁶Campus Biotech - Geneva - Switzerland, Geneva, GE, Switzerland

Keywords

Occupational Training; Action Video Games; Psychomotor Learning

Abstract

Action video game playing has been linked with enhanced cognitive and perceptual abilities measured via a variety of basic psychological lab tests. However, much less work has examined such relations in the context of measures with direct real-world workplace relevance. Here we examined the performance of male United States military personnel on a psychomotor task battery, part of an official selection test designed to assess aptitude for military aviation. We found that action video game playing was significantly and positively associated with performance on this battery. More specifically, increased action video game experience among Naval Flight Students was linked to both better initial performance as well as more rapid learning within the psychomotor task. In contrast, when examining the same associations in a control group for whom the psychomotor task was not occupationally relevant (i.e., not Naval Flight Students), action video game playing was not reliably associated with psychomotor task learning. Time spent playing recreational video games with mechanics more similar to the screening task, flight simulator games, was not related to psychomotor task learning speed in either group. This pattern suggests that recreational action video game playing may work in concert with explicit occupational training to support effective learning and successful workplace outcomes in high-stakes professions.

Everyday impacts of action video game playing – Occupational screening for high-stakes professions

Introduction

The demands of the 21st century workforce necessitate constant learning and expertise acquisition on the part of individuals. Indeed, it is estimated that the average US worker today will change jobs between 12 and 13 times in their lifetime, with about 1 in 4 of those job changes being part of a broader full career change (unmuld.com, 2022; zippia.com, 2023). Each of these job changes will, in turn, necessitate a sizable amount of new learning – including everything from new terminology, to new technology, to entirely new skill sets. This constant pressure for adaptability calls for a better understanding of the factors that may facilitate such flexibility.

To-date most basic science research examining predictors of this type of adaptability has focused on individual-level traits or constructs. This includes, for instance, the construct of intelligence, which has at its core the ability to learn from experience and efficiently adapt to new contexts (Binet & Simon, 1916; Carroll, 2004; Rohde & Thompson, 2007). Perhaps not surprisingly then, measures of intelligence, and in particular fluid intelligence, have been shown to be excellent predictors of success in the workplace (Amdurer et al., 2014; Bertua et al., 2005; Kuncel et al., 2004). A host of other constructs, many of which are related to or are thought to partially underpin intelligence, have similarly been shown to be associated with successful careers. These include working memory and various executive functions (Diamond, 2013; Mashburn et al., 2023).

There is considerably less work though on specific life experiences (outside of formal education) that might be related to the ability to learn and develop new abilities. One such experience that has been put forward is playing first or third-person commercially-available shooter games (together referred to as “action video games”). In correlational studies, playing action video games has been associated with better performance in a wide range of cognitive functions, including in perception, top-down attention, and task-switching (Chisholm et al., 2010; Donohue et al., 2010; Dye et al., 2009; Green & Bavelier, 2003, 2007; Hubert-Wallander et al., 2011). All told, meta-analytic work has shown that individuals who, as part of their regular daily life, have played 3 or more hours per week of action video games for at least 6 months outperform individuals who report playing fewer than 3 hours of video games by around 2/3rd of a standard deviation across all measures of cognitive function combined (Bediou et al., 2018, 2023).

Importantly, intervention studies have further established that the relationship between action video game play and enhanced cognitive function is causal. That is, it is not simply the case that people who are born with better cognitive functions choose to play action video games disproportionately. Across a number of studies, individuals (who had rarely or never played

video games previously) were asked to play either action video games (experimental group) or non-action video games (control group) for 30-50 hours. While both groups showed improvements on the games they played, those in the action video game group showed disproportionate improvements in basic vision (e.g., contrast sensitivity) and visual attention (e.g., as measured by visual crowding, visual search, or multiple object tracking paradigms), more agile task-switching and multitasking abilities, and better decision-making, amongst other skills, as compared to the control group that played non-action video games (Feng et al., 2007; Green et al., 2010; Green & Bavelier, 2003, 2006, 2007; Strobach et al., 2012). Meta-analytic work has again confirmed the beneficial, causal impact of action video game training on cognition, with estimates of the benefit being around $1/3^{\text{rd}}$ of a standard deviation (Bediou et al., 2018, 2023; noting that this magnitude depends highly on factors such as the particular cognitive domain, the amount of training, etc; although see Sala et al., 2018 for an opposing view of the field).

Interestingly, the finding that action video game experience produces benefits not just on the games themselves, but on basic measures of cognitive function that do not bear direct resemblance to action video games, runs counter to much of the literature on human learning (Maniglia & Seitz, 2018). This state of affairs is most tellingly illustrated by the case of perceptual learning, where the benefits of training are typically reasonably tied to the specifics of the trained task (Fahle, 2004). For instance, individuals trained to judge offsets of vertically aligned boxes will improve in that ability (i.e., will be able to do the task with smaller and smaller offsets), but if the boxes are subsequently changed to be aligned horizontally, they'll frequently show no advantage of the previous training (Snell et al., 2015). In other words, the benefits of training are specific to the trained orientation, failing to generalize to new orientations. What makes action video game training unique, then, is that individuals show improvements not just on the action video games themselves, but also on tasks that are far more dissimilar to action video games than are, for instance, horizontally aligned boxes and vertically aligned boxes (e.g., psychology lab tasks using letters, dots, lines, gratings, etc.). Indeed, most theories of learning assume that near transfer or transfer to tasks closely related to the trained one is much easier to induce than far transfer or transfer to tasks that share fewer characteristics with the trained one (Barnett & Ceci, 2002; Perkins & Salomon, 1992). As such, it is the degree of far transfer induced by action video game experience that has made it of interest both from a theoretical and a practical perspective.

Two possibilities for how action video game-related enhancements manifest have been considered (Bavelier & Green, 2025). The first possibility is that the rich array of skills challenged by action video game play taps certain shared constructs with laboratory-designed tasks and thus directly transfers to different aspects of cognition. This predicts that the benefits of previous action video game play will be seen right away, from the very moment an individual encounters a new task. Alternatively, it could be that action video game play facilitates

adaptability or the learning of novel tasks or contingencies – in other words, produces “learning to learn.” In this case, the benefits of action video game play would be expected to manifest as faster learning or greater learning gains on new cognitive tasks. Of note, these two mechanisms are certainly not mutually exclusive and could be simultaneously at play.

While most of the early results in the action video game field were interpreted as direct transfer, it was also the case that tasks and data analyses were not designed to adjudicate between these alternatives. As researchers have, in the recent years, started to design tasks to more clearly differentiate direct transfer and learning to learn, evidence is accruing suggesting that the learning to learn mechanism accounts for at least part of the benefits that arise from action video game play. For example, in one recent action video game intervention, participants were compared on two learning tasks, one a perceptual learning task and the other a cognitive learning task, after 45 hours of training on either action video games or on control video games (Zhang et al., 2021). The two groups showed reasonably similar initial performance on the two learning tasks. However, those individuals who had trained with action video games showed significantly faster improvements in performance through time. Additional support for the idea that action video games foster learning to learn has been found in laboratory settings testing perceptual, visuo-motor control and working memory learning (Bejjanki et al., 2014; Gao et al., 2024; Gozli et al., 2014).

Yet, despite the fact that the effect sizes produced by action video games are of a magnitude that they would be predicted to have real-world value, the literature focused on real-world-relevant outcomes is limited. A few studies point to the potential value of video game play for surgeons, in particular laparoscopic surgeons (Ou et al., 2013; Rosser et al., 2007; Schlickum et al., 2008). Yet these studies remain quite scarce and of high heterogeneity. Other studies point to video game play, and especially action-video game play, as a tool to facilitate learning to read in children (Pasqualotto et al., 2022; Peters et al., 2021; Puccio et al., 2024). But, virtually none of the more real-world focused research has examined whether any observed benefits are better described as direct transfer, learning to learn or a mix of both.

There is thus a clear need for additional work examining the extent to which action video game experience is associated with direct transfer, learning to learn, or both, in measures of more real-world relevance. The present work does so by leveraging an experiment performed with active duty military personnel who repeatedly performed a subset of the Aviation Selection Test Battery (ASTB) and also completed a survey regarding their video game experience. The ASTB is a screening tool used by the United States Navy, Marine Corps, and Coast Guard to identify prospective candidates for officer aviation training programs. A component of the ASTB is the Performance Based Measures (PBM) battery, which was introduced in 2013 to assess specific skills and abilities identified as relevant to aviation aptitude (Walker et al., 2007). The purpose of the PBM is to evaluate candidates’ “physical dexterity, eye-hand coordination, and ability to

divide attention among different tasks” through the administration of increasingly challenging tracking subtasks performed concurrently with other cognitively demanding tasks (NAMI, 2024). That military-centered occupations could be an interesting early testbed to examine potential real-world positive applications of video game training (and or the use of video game expertise as a predictor of performance) has been suggested by a host of research groups, noting, for instance, various shared demands between video gaming and those occupations (e.g., need for speeded decision-making; McKinley et al., 2011; Sharpe et al., 2025).

While the individual subtests of the PBM battery are strong predictors of future aviation training performance (Sibley, 2024), conventional analyses that only rely on aggregated performance metrics may miss valuable insights regarding within-task and across-task learning. We therefore sought to investigate performance on the PBM as a task that not only measures present abilities, but also captures learning capabilities. To this end, we leverage recent work (Clarke & Hunt, 2025; Cochrane et al., 2023; Cochrane & Green, 2023) that has shown that most tasks where participants’ experience unfolds through time (e.g., 64 trials of a working memory task or 100 trials of an executive function task) can be thought of, and effectively modeled, as learning tasks. This, combined with information concerning video game habits, allowed for the examination of whether previous action video game experience was associated with either immediately better performance and/or faster learning on the PBM battery. Of note, our dataset included two distinct participant populations: the first group comprised Naval Flight Students, who were selected for aviation training based, in part, on their performance on the ASTB. Therefore, this group was expected to demonstrate higher baseline proficiency in the skills and abilities assessed by the PBM battery. In contrast, the other group was enlisted service members pursuing aviation-related roles, who were likely less familiar with the type of skills the PBM battery taps.

In summary, our aim here was to test the extent to which action video game play may facilitate direct transfer and/or learning to learn in an ecologically valid context. By modeling initial performance and score progression through these series of tests, we assessed how these aspects of performance correlated with participants’ action video game history. If greater action video game play history was found to be associated with better performance at the very start of the task, this would indicate direct transfer; conversely, if greater action video game familiarity was found to be linked to a faster progression rate as the task proceeds, this would support learning to learn (as above, it is important to note that the two effects are not mutually exclusive; both could be present simultaneously).

Of further interest was the contrast between the effect of action video game familiarity and that of flight simulator game familiarity. At stake here is the issue of transfer of training. On the one hand, one may expect flight simulator game familiarity to be more aligned with the skills tested by the PBM battery than action video game play. At its core the ASTB was designed to select individuals predicted to be successful in military aviation school. This would in turn result in the

prediction that performance on the PBM battery should be more related to flight simulator game experience than to action video game experience. On the other hand, the well-documented fact that training gains tend to be highly specific suggests that flight familiarity may not necessarily easily transfer to this test. In contrast, the benefits of action video game play have been noted to transfer to other novel tasks, especially in the perceptual, cognitive and motor domains (Bavelier et al., 2012; Bavelier & Green, 2025). If so, this would predict action video game experience may be more related to PBM battery performance than flight simulator game experience.

Methods

Participants

Active duty military personnel ($N = 461$) stationed at Naval Air Station Pensacola consented to participate in this study that took place over two days. Participants were not compensated in any way for their participation, which was voluntary. Due to scheduling constraints, 183 participants were unable to return for the second session, which occurred exactly one week after the first. An additional 13 participants were removed for poor performance. This left 265 participants, of whom 25 were female. Sex was determined by self-reported survey responses, in which participants were provided the option of male or female, or to skip responding. Although an original goal was to examine variations between males and females in learning with relation to video game playing, the highly skewed proportions led us to be concerned about biased inferences. As such, we focused our analysis only on the male participants, resulting in a final sample of 228 participants (Age $M = 23.81$ years, $SD = 3.38$). The data we report here is a subset of that reported in Draheim et al. (2025), in which the authors did not address links between action video game playing and rates of learning within the PBM. Naval Research Laboratory's Institutional Review Board approved this protocol: NRL.2021.0003. This work was not preregistered.

These 228 participants were in turn categorized as belonging to one of two groups. The first group ($n = 128$) comprised Naval Flight Students (referred to below as *flight students*) who had been selected for flight training, and had therefore taken the ASTB at least once. The flight students had not yet started training. The second group ($n = 100$) comprised enlisted U.S. Navy and Marine Corps personnel in training for roles as Aviation Ordnancemen, Aviation Structural Mechanics, and Naval Air Crewmen (referred to below as *naive*). Overall, 75% of the sample reported some college experience. Data were available for 116 of the 128 flight students regarding the time interval between their most recent official ASTB attempt and participation in this laboratory study. The median time interval was 665 days ($SD = 415$ days) with a range of 157 - 2491 days. For the sample of naive participants, this was their first exposure to the PBM battery.

Procedure

Data were collected during two sessions, separated by one week, within a controlled laboratory environment at U.S. Naval Air Station Pensacola, Florida. The laboratory was equipped with 20 standardized computer stations, each comprising a 24-inch monitor, a Logitech X52 flight control system (consisting of a left-handed throttle and right-handed stick controller), and stereo headphones (noting here that this system is quite different from a standard video game controller or keyboard). Each session lasted approximately three hours, for a total of six hours over two sessions. Sessions commenced with eye-tracking calibration and two brief eye tracking tasks, not pertinent to this project. Subsequently, participants were instructed how to log in to the Navy's official ASTB testing platform. Participants were then informed that they would complete three consecutive rounds, or "blocks," of a modified version of the Aviation Selection Test Battery's (ASTB) Performance Based Measures (PBM) battery, described in detail below.

Upon completion of each PBM block, participants received a score and were instructed to write it down and wait for the rest of the group to finish that block. Participants then engaged in a group discussion facilitated by the experimenter, focusing on that block's scores, with the intent of fostering engagement and motivation. Following the third PBM block, participants completed a video game survey (see Supplementary Materials) and a battery of cognitive tests not relevant to this project. The second session largely replicated the general task sequence of the first session, beginning with the eye tracker setup, followed by three blocks of the PBM, and commencing with additional cognitive assessments, also outside the scope of this project.

Tasks

The Iterative PBM

The Naval Research Laboratory and Naval Aerospace Medical Institute collaborated to build an experimental, repeatable version of the Navy's PBM battery, henceforth referred to as the Iterative PBM. The intention of this modified version was to investigate within-task learning across repeated engagement with the psychomotor tracking subtasks. Given this focus, we excluded the PBM's direction orientation subtest, but all other subtasks within the Iterative PBM were identical to those experienced by official ASTB test takers. The original PBM subtest instructions were adapted to enhance participant comprehension and to explicitly address the iterative nature of the task.

The Iterative PBM encompasses six subtests administered sequentially during each block: dichotic listening test (DLT), vertical tracking test (VTT), 2-dimensional aviation tracking subtask (ATT), two-handed tracking subtask (ATTVTT; see Figure 1), two-handed tracking with dichotic listening subtask (ATTVTDLT), and two-handed tracking with emergency scenarios subtask (ATTVTSCN). In the initial block of each session (i.e., blocks 1 and 4) participants

receive self-paced instructions and a 30-second unscored practice period for each subtest, with the exception of the ATTVTTSCN, which mirrors the official test procedure by omitting practice. Abbreviated instructions, with no practice, are provided in subsequent blocks (blocks 2 and 3) of each day. The duration of the scored portion of each subtask varies, as shown in Table 1. The following section provides details about each subtask within the Iterative PBM. Further information regarding the official PBM tasks and their validation can be found in Phillips et al. (2011) and Walker et al. (2007).

Iterative PBM Subtask	Phase	Time to complete
Dichotic Listening (DLT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	120 seconds
Vertical Tracking (VTT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	60 seconds
2-Dimensional Airplane Tracking (ATT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	60 seconds
Two-Handed Tracking (ATTVTT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	120 seconds
Two-Handed Tracking + Dichotic Listening (ATTVTDLT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	180 seconds
Two-Handed Tracking + Emergency Scenario (ATTVTSCN)	Instructions	Self-paced
	Scored	120 seconds

Table 1. One block of the Iterative PBM showing the context in which our 4 subtasks of interest (ATT, ATTVTT, ATTVTDLT and ATTVTTSCN) were administered. Participants performed six such blocks, three on their first day of testing and three on their second day of testing. Instructions and practice were only given during the first block of each day (block 1 and 4); condensed instructions and no practice were given on blocks 2, 3, 5, and 6.

Dichotic Listening (DLT)

During the dichotic listening test (DLT), participants wear stereo headphones and listen to auditory stimuli consisting of serially presented letters and numbers. During the task, participants keep their left hand on the throttle and their right hand on the stick and are instructed to selectively attend to only one ear for 30 second blocks of time. They respond to odd numbers by pressing the throttle button and even numbers by pressing the stick button. Within this Iterative PBM, the DLT is administered initially for 120 seconds to familiarize participants with the subtask, because it is performed later in the Iterative PBM with a tracking subtask. DLT performance data were collected, but fall outside the scope of this analysis.

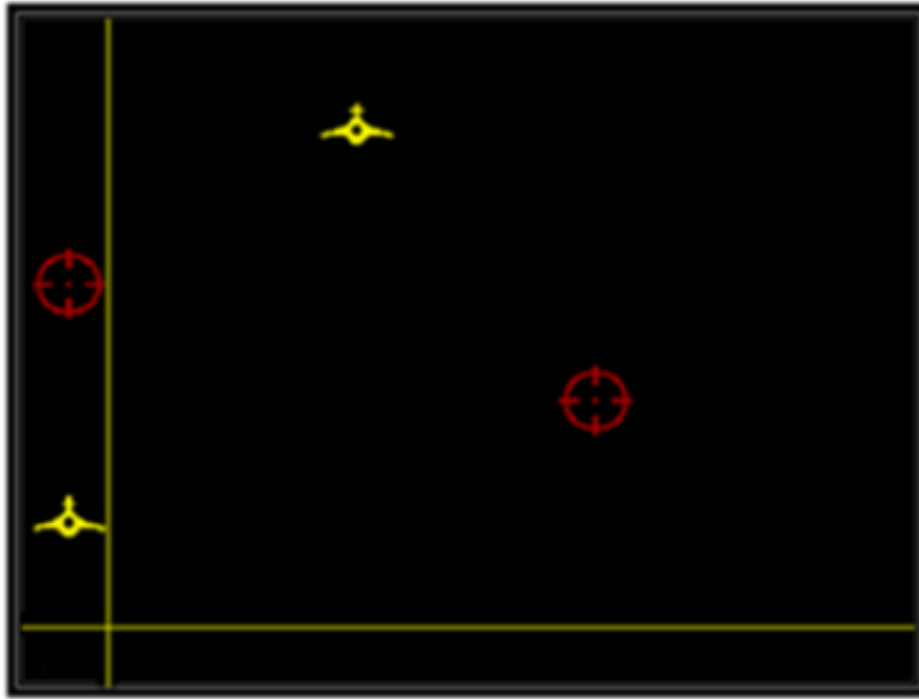


Figure 1. Task schematic. Illustration of the ATT-VTT task which combines vertical tracking with 2-d tracking. The target is the yellow airplane and the tracker is the red crosshair.

Vertical Tracking (VTT)

The vertical tracking subtask (VTT) requires participants to track a yellow airplane moving along the Y-axis on the left hand side of the display (see the leftmost section of Figure 1). During the instruction phase, participants are directed to place their left hand on the throttle, which controls the movement of the red crosshair, and to attempt to precisely track the movement of the yellow airplane. The yellow airplane's trajectory involves bouncing off the top and bottom boundaries of the display and changing vertical direction after being tracked closely for a specified duration (note that specific information is withheld to maintain the integrity of the operational test). Following self-paced instructions and a 30-second unscored practice period, participants complete 60 seconds of tracking. During this period, the speed of the yellow airplane (i.e., task difficulty level) increases at the 20 and 40-second marks.

2-Dimensional Airplane Tracking (ATT)

In the 2-dimensional airplane tracking subtask (ATT) participants are tasked with tracking a yellow airplane moving in straight lines, across two dimensions (horizontally, vertically, and diagonally), in the main part of the display (see Figure 1). Participants are instructed to position their right hand on the control stick, which controls the movement of the red crosshair. The stick's Y-axis controls are inverted, such that moving the stick forward moves the crosshair upwards on the display, while pulling the stick back moves the crosshair downwards on the display. The yellow airplane moves in straight lines and reflects off the display boundaries, and it

also changes direction after being tracked closely for a specified duration. Following self-paced instructions and a 30-second unscored practice period, participants complete 60 seconds of tracking. During this period, the speed of the yellow airplane increases at the 20 and 40-second marks.

Two-handed Tracking (ATTVTT)

The two-handed tracking subtask (ATTVTT) requires participants to simultaneously perform the VTT and ATT, as shown in Figure 1, with the left hand on the throttle and right on the stick. Participants are given instructions, followed by a 30-second practice period, and 120-second scored phase where the speed of the airplanes increase at the 40 and 80-second marks.

Two-handed Tracking with Dichotic Listening (ATTVTDLT)

The two-handed tracking with dichotic listening subtask (ATTVTDLT) requires participants to do the ATTVTT while simultaneously performing the DLT. Participants are given instructions, followed by a 30-second practice period, and 180-second scored phase where the airplane speeds increase at the 60 and 120-second marks.

Two-handed Tracking with Emergency Scenarios (ATTVTSCN)

The two-handed tracking with emergency scenarios subtask (ATTVTSCN) requires participants to perform the ATTVTT while simultaneously responding to three randomly presented emergency scenarios. These scenarios require rapid execution of specific response sequences, involving a combination of button presses and knob adjustments, as explained during the instructional phase. Participants are given instructions, followed by a 120-second scored phase where the airplane speeds increase at the 40 and 80-second marks.

The DLT and VTT subtasks are not included in the model presented in the results, as they were simple enough that most participants performed near asymptotic performance, leaving little room for learning to be observed.

The performance measure used for each of the Iterative PBM's tracking subtasks was the Euclidean distance between the target and the crosshair. This distance, which we will hereafter refer to as *tracking error*, was recorded at a rate of 5 samples per second. These errors were downsampled by dividing each of the subtasks' difficulty levels' recording durations into 10 equally-spaced time windows, thereby leading each subtask for each block to be reflected by 30 tracking error values. Across all difficulties, subtasks, and blocks, each participant thus had 900 tracking error values (i.e., 10 tracking errors for each of 3 difficulties, on 5 subtasks with 6 blocks each).

Surveys

The video game survey was modelled after the Bavelier lab video game questionnaire (Bavelier, 2022) and used to capture experience with specific genres of video games during adulthood and childhood. As such, the survey included two overarching questions: the first asked participants to respond based on their gaming activities during the last 12 months, while the second question directed participants to respond based upon their gaming activities from ages 3 - 13. For each question, participants were told “for each type of game, specify the number of hours played per week when you played the most” and listed nine independent genres of video games, including the same eight game genres as Bavelier’s (First/Third-Person Shooters, Action-RPG/Adventure, Sports/Driving, Real-Time Strategy/MOBA, Turn-Based/ Non-Action Role-Playing/Fantasy, Turn-Based Strategy/Life Simulation/Puzzle, Others) in addition to Flight Simulator Games. Participants were given six ordinal options to choose among for responses: “Never,” “Less than one hour,” “Between 1 and 3 hours,” “Between 3 and 5 hours,” “Between 5 and 10 hours,” and “More than 10 hours,” which we coded as a 0 to 5 scale. See the Supplementary materials for a copy of the survey. To calculate a continuous score of action video game experience we summed the coded scores from the following genres for both the childhood and adult questions: First/Third-Person Shooters; Action-RPG/Adventure; Sports/Driving; Real-Time Strategy/MOBA. This resulted in one score per participant that could range from 0 to 40.

Participants also responded to a flight experience survey that included questions related to any actual logged flight hours and flight simulator experience (both professional and recreational). We were interested in the relative links between actual flight experience and Iterative PBM tracking error, however, the overwhelming majority of naive participants had zero flight experience, and no experience with professional-level flight simulators. Therefore, in order to compare groups we used the summed score of flight simulator game experience, from the video game survey, across childhood and adulthood; this led to a score that could range from 0 to 10.

Modeling

Changes in tracking error through time were modeled as an exponential function of experience duration on the task (Cochrane, 2020; Cochrane & Green, 2021; Doshier & Lu, 2007; Heathcote et al., 2000; Kattner, Cochrane, & Green, 2017). We estimated these trajectories of change using Bayesian generalized nonlinear mixed-effects regression (Bürkner, 2017; Clarke & Hunt, 2025; Cochrane et al., 2024) using the **brms** package in R. Priors were minimally informative and had no influence whatsoever on participant-level estimates of parameters, which were the primary values of interest (see Supplement for model specification). A 3-parameter saturating exponential function was specified by modeling starting tracking error, asymptotic tracking error, and the shape of the exponential curve (parameterized as a time constant defining the amount of time taken to proceed 50% of the way from the start to the asymptote; we refer to this as the *time-to-learn* parameter). Asymptotic tracking error represents the error level approached with an infinite amount of practice, or in other words, how well a participant would perform if we were to allow them an arbitrarily large amount of time on the task.

We note that several features of the data led us to make certain choices in model specification. First, starting tracking error and asymptotic tracking error were defined according to a linear model structure including a fixed effect contrast between flight students and naïve participants as well as a fixed effect of subtask and difficulty (i.e., speed of the target) within subtask, thereby accounting for the broader structural differences in start and end performance assumed with subtasks of varying difficulties. In contrast, time-to-learn was specified according to a linear mixed-effects structure including a fixed contrast between flight student and naïve participants, but not subtask and difficulty. In doing so, we assume a common time-to-learn across the four subtasks of interest for each participant. Second, given our interest in individual-level learning estimates, a by-participant random intercept was also added to starting tracking error and time-to-learn. Because learning unfolded slowly relative to the measured timescale (Draheim et al., 2025), we conservatively did not estimate by-participant values for asymptotic performance. In doing so, we assume that participants, for a given subtask, difficulty level and group, arrived at the same asymptotic performance. While unlikely to be true, strictly speaking, we believe that this was a worthwhile simplification for the sake of maintaining model estimability and robustness of our other by-participant parameters. In sum, nested within the exponentially-decaying nonlinear generalized model (Cochrane et al., 2024), the following linear mixed-effects models were used: (i) starting tracking error = group (2 level fixed effect) + subtask (4-level fixed effect) * difficulty (3-level fixed effect) + participant-level random intercept; (ii) time-to-learn = group (2 level fixed effect) + participant-level random intercept; (iii) asymptotic performance = group (2 level fixed effect) + subtask (4-level fixed effect) * difficulty (3-level fixed effect).

We modeled the median values of tracking error as a function of time on task (i.e., using the asymmetric Laplace distribution and likelihood function in **brms** with the estimated quantile fixed to be .5, due to our lack of knowledge of the true generative distributional properties of the tracking error measure). In addition, although the median was being estimated, it remained necessary to estimate a dispersion parameter; this dispersion parameter was modeled as a log-linear function of time.

For full model specification and fixed-effects posterior distributions see Supplement. Tests of parameter reliability (e.g., comparing naïve to flight student) were conducted by identifying whether the relevant parameter's posterior distribution 95% credible interval (CI) included zero. Subsequent associations with video game playing measures used participant-level estimates and were tested with bootstrapped rank correlations, wherein we assessed whether the 95% confidence intervals included zero, or with linear regression models. All tests were two-sided, and all tests were designed such that the data would meet the assumptions of each test.

We also estimated a model with the same distributional assumptions as our model of learning but with no change estimated over time; in this non-learning model the unchanging median tracking error was estimated using the same mixed-effects formula as the starting value described above ; (i) $\text{tracking_error} = \text{is_NFS} + \text{subtask} * \text{difficulty} + (1 | \text{ID})$. This non-learning model acts as a baseline model against which the learning model can be quantitatively compared in order to assess goodness-of-fit.

Results

1. Descriptive results for each group and tracking subtasks

We plot below (Figure 2) the performance as measured by tracking error, such that lower values correspond to better performance. As expected, flight students were overall better than naive participants. Dividing participants into tertiles, we see that this effect is visible across all performance levels. Moreover we see that, as expected, performance is best for the simplest ATT subtask and then worsens as multi-tasking becomes more complex (see also Table 2) - i.e., first when the 2-d tracking subtask of ATT is combined with the 1-d tracking subtask VTT to create the ATTVTT, then adding a third dichotic listening subtask (ATTVTDLT) and finally replacing that dichotic listening subtask by an even more demanding tracking subtask mirroring emergency scenarios (ATTVTSCN). Finally, Figure 2 also highlights a considerable amount of improvement over the course of the experiment on each of our 4 tracking subtasks of interest and in each group of participants. Indeed, top tier flight students, even though clearly outperforming all other groups, still exhibit noticeable performance improvement.

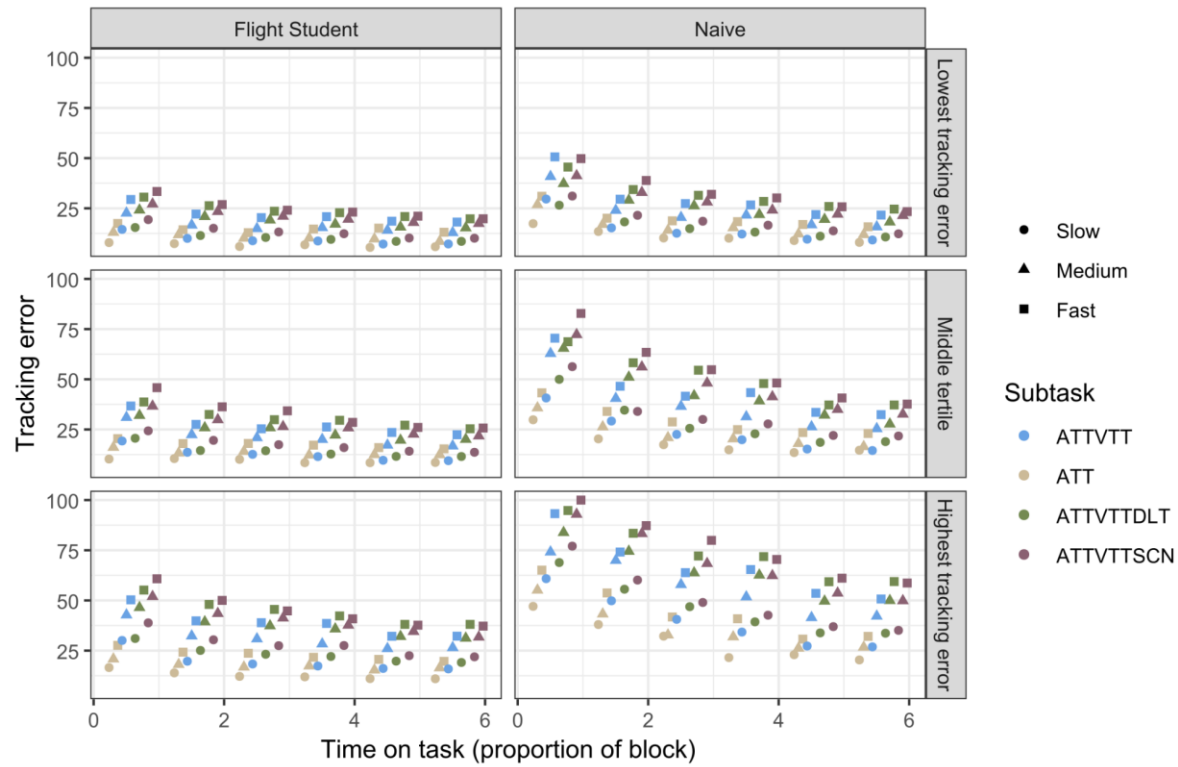


Figure 2. Tracking error over the course of the experiment. The x axis represents the corresponding block number. Values between 0 and 1 come from participants ($n = 228$) completing the first block, values between 1 and 2 completing the second block, and so on. Vertical panels separate flight students and naïve participants. For each of these, horizontal panels separate participants, within flight student and naïve, who performed in the best tertile, the middle tertile, or the worst tertile of overall average tracking error. Colors indicate subtask, while shapes indicate the within-subtask difficulty. Each point is the geometric mean of tracking error aggregated within that participant group, block, subtask, and difficulty.

2. Evidence for learning on the subtasks

Tracking error was seen to decrease over time in each of the 4 key tracking subtasks. The change between block 1 and block 6 broken down by group and subtasks can be seen in Table 2.

GROUP	SUBTASK	BLOCK 1 MEAN	BLOCK 6 MEAN	CHANGE CI ₀₂₅	CHANGE CI ₉₇₅
FLIGHT STUDENT	ATT	26.74	18.52	-10.51	-5.93
NAÏVE	ATT	56.41	28.48	-31.88	-23.98

FLIGHT STUDENT	ATTVTT	39.51	22.64	-19.44	-14.29
NAÏVE	ATTVTT	68.6	34.15	-37.58	-31.31
FLIGHT STUDENT	ATTVTTDL	40.4	25.59	-16.84	-12.79
NAÏVE	ATTVTTDL	69.94	39.99	-33.23	-26.66
	T				
FLIGHT STUDENT	ATTVTTSC	50.91	28.57	-24.5	-20.18
NAÏVE	ATTVTTSC	81.74	42.07	-43.28	-36.05
	N				

Table 2. Mean Block 1 and Block 6 tracking error by group for each of the 4 subtasks of interest. The 95% CI of the change in distance (i.e., block 6 minus block 1) was calculated by first averaging within each participant ($n = 228$), subtask, and block, calculating change scores, and then calculating the bootstrapped CI of change scores.

Our Bayesian modeling confirms and qualifies such learning (see Figure 3). The Bayesian nonlinear mixed-effects model converged ($R\text{-hat} < 1.05$ for all parameters). When comparing the model that included learning over time to the model with no learning, the model with learning performed much better. The Leave-One-Out Information Criterion (LOOIC) indicated a large improvement in predictive power ($\Delta\text{LOOIC} = -35481 \pm 8.9$; values less than -4 are conventionally considered to indicate meaningful differences in model predictiveness; Vehtari et al., 2017). A heuristic effect size can be calculated by observing the rank correlation between the null model fitted values and true distances ($\rho = .66$) and the learning model rank correlation ($\rho = .72$). Note that the null model already captures much of the variation in errors due to the large differences between participants, subtasks, and difficulty levels. A naive pseudo- ΔR^2 , found by squaring the above ρ values and then taking the difference, would indicate an additional 7.6% of variance explained by adding a learning component to the model.

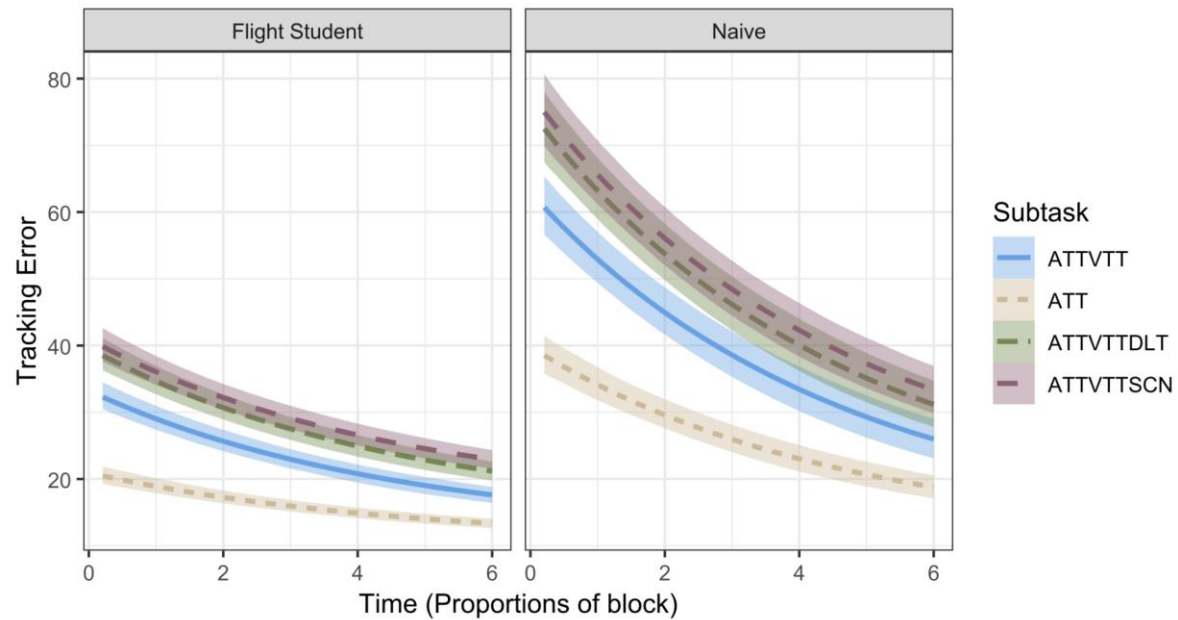


Figure 3. Model fit trajectories of change. Trajectories show median distance-to-target plotted separated by group and subtasks. Note the model was run over the whole sample ($n = 228$) with group and subtasks as factors. Shaded areas indicate 95% CI.

3. Learning characteristics per group and subtask

In examining the posterior distributions of the fixed-effects coefficients quantifying the differences between naïve and flight student groups, we observed that the flight student group started with smaller median tracking error (posterior distribution mean initial tracking error = 32.14) than the naïve group (60.56) leading to a group differences (-28.42; $CI_{95} = [-33.48, -23.74]$; see Figure 4 & Table 3). When calculating a Cohen's d for an approximate effect size, using the by-participant distance values plotted in Figure 4, the approximate Cohen's d was of large size at 1.64. There was no reliable difference in time-to-learn across groups (0.05; $CI_{95} = [-0.61, 0.73]$; approximate $d=0$, see Figure 4). Finally, albeit modeled only at the group level and not the individual level, the flight student group had asymptotically lower tracking error than the naïve group (-0.62; $CI_{95} = [-1.11, -.14]$).

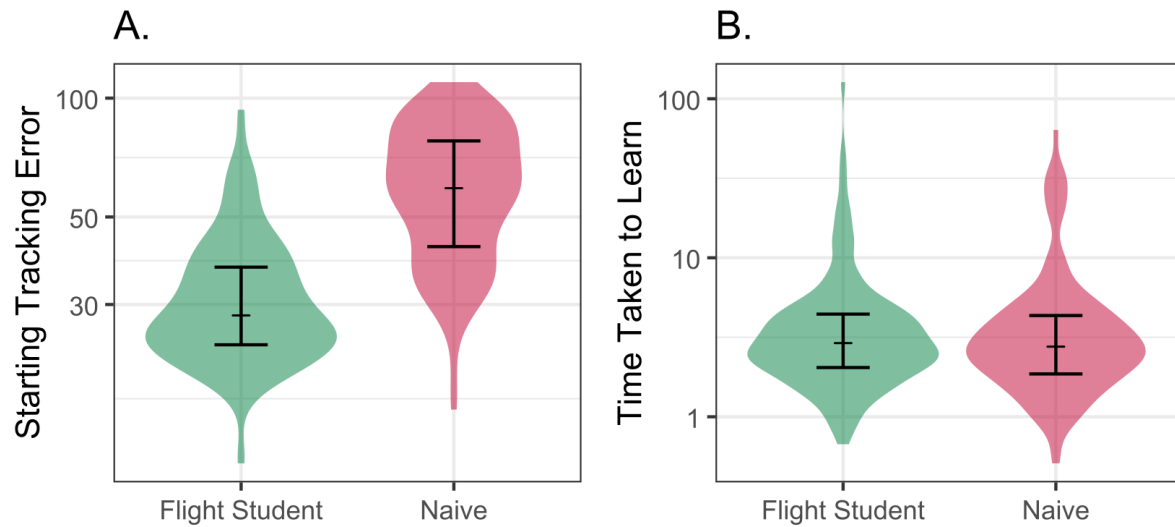


Figure 4. Distributions of by-participant estimates. Model parameter estimates include [A] starting tracking error and [B] time-to-learn (each y axis is on a loglinear scale; $n = 228$). For the statistical comparison of groups using model posterior distributions see the main text. Asymptotic error is not shown because by-participant values were not estimated. Lines indicate means and 95% CI.

In addition, we observed that the by-participant correlations between starting tracking error and time-to-learn were $\rho=0.45$ for the flight student group and $\rho=0.30$ for naïve participants. That is, in each sample we observed non-trivial correlations such that participants who started better on the task also learned faster, although these two dimensions of performance were far from isomorphic. This pattern further supports the separate examination of the two groups' performance separately.

Finally, learning varied by subtasks, with the starting tracking error being larger as the subtask became harder as expected and shown in Table 3. Similarly, asymptotic tracking error grew as subtask difficulty increased (Table 3).

Subtask	Starting Error	Starting Error CI ₀₂₅	Starting Error CI ₉₇₅	Asymptotic Error	Asymptotic Error CI ₀₂₅	Asymptotic Error CI ₉₇₅
ATT	28.11	26.67	29.51	10.74	10.19	11.29
ATTVTT	44.28	42.09	46.38	11.99	11.42	12.55
ATTVTDLT	52.87	50.23	55.30	14.53	13.91	15.14
ATTVTTSN	54.68	51.91	57.26	16.49	15.84	17.12

Table 3. Model fit parameters for each subtask, (estimated across groups and across the three speed levels; $n = 228$) at an overall [intermediate] level relative to subtask difficulty and participant group.

4. Action video game play and flight simulator experience related to starting performance and time-to-learn in the flight student group

We found reliable relationships between experience in action video games and both starting tracking error ($\rho = -0.31$ $CI_{95} = [-.47, -.14]$), wherein those with more action video game experience showed lower starting tracking error, and time-to-learn ($\rho = -0.35$ $CI_{95} = [-.49, -.19]$), wherein those with more action video game experience showed faster learning (see Figure 5).

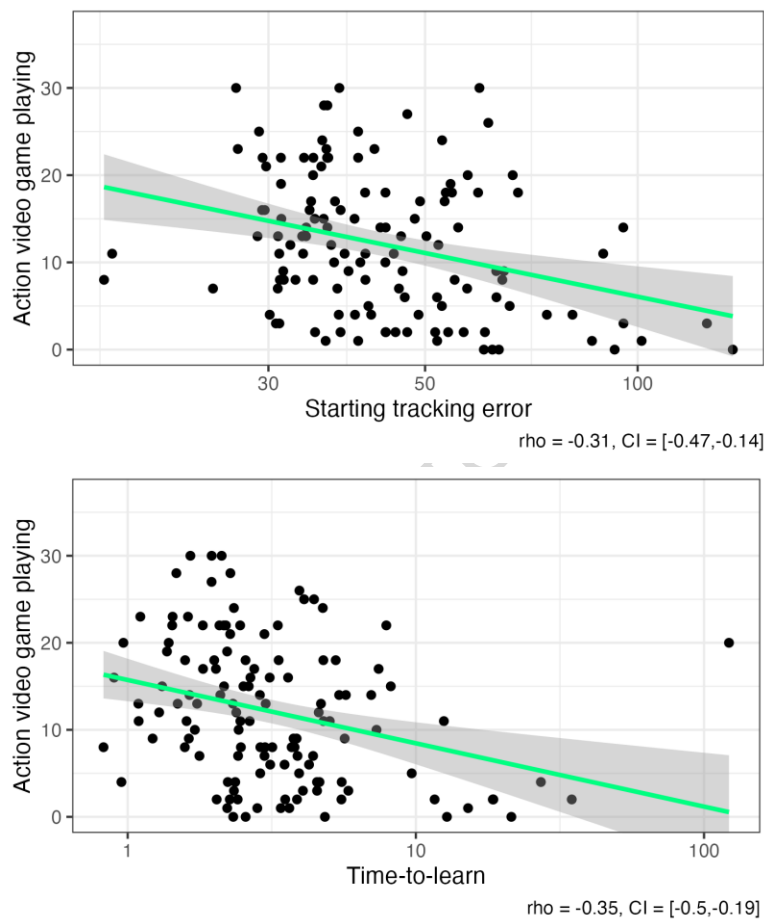


Figure 5. Rank correlations between learning and action video game playing in flight student participants ($n = 128$). Reliable correlations were observed between action video game playing and starting tracking error (top panel) and time to learn (bottom panel). Linear trends and 95% CI overlaid for demonstration purposes.

In the case of flight simulator experience, a correlation with starting tracking error was apparent as well ($\rho = -0.21$ $CI_{95} = [-.37, -.04]$; see Figure 6) but a reliable association was not evident with time to learn ($\rho = -.09$ $CI_{95} = [-.26, .08]$; see Figure 6).

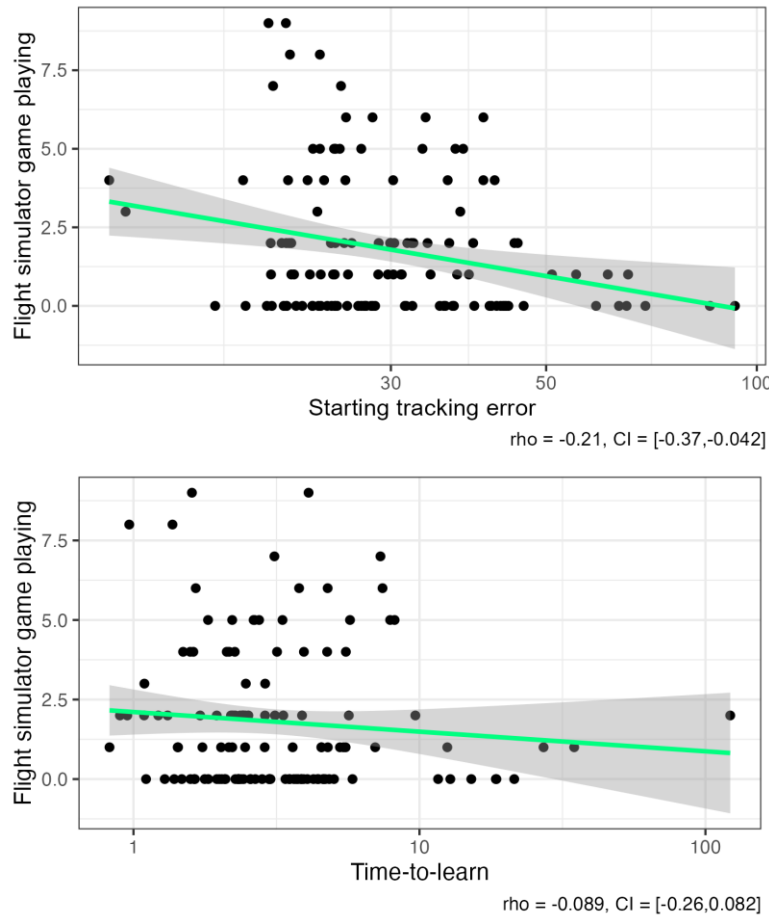


Figure 6. Rank correlations between learning and action flight simulator game playing in flight student participants ($n = 128$). A reliable correlation was observed between flight simulator game playing and starting tracking error (top panel) but not time to learn (bottom panel). Linear trends and 95% CI overlaid for demonstration purposes.

5. Action video game play and flight simulator experience related to starting performance and time-to-learn in the naïve group

In the naïve participants, whose overall performance was worse (i.e., higher error, see Figure 2), we observed numerically reduced and non-significant correlations between starting tracking error and action video game experience and time to learn and action video game experience (Figure 7). Although an explicit group comparison was not of primary interest to this study, we next fit a Bayesian linear regression model predicting rank-transformed and z-scored time to learn with the binary group affiliation, rank-transformed action video game playing, and their interaction. Action video game playing, as a predictor, was rank-transformed and then z-scored within each group separately to avoid any collinearity confounds between group and action video game playing. Model fitting used the **brms** package with default priors. We found that the interaction

term was reliable such that flight students' link between time to learn and action video game playing was more negative than naïve participants ($b = -.31$, $CI_{95} = [-.57, -.05]$). In this model, the main effect of action video game playing was reliable ($b = -.17$, $CI_{95} = [-.29, -.04]$) and the main effect of flight student membership (i.e., binary group variable) was not reliable ($b = .06$, $CI_{95} = [-.19, .31]$). See Figures 5 and 7 for visualizations of the slopes linking action video game playing and time to learn in each of the groups separately. In a comparison with an identical model, but dropping the interaction term, the model with the interaction term had a modestly larger amount of evidence (Bayes Factor estimated via bridge sampling = 5.04).

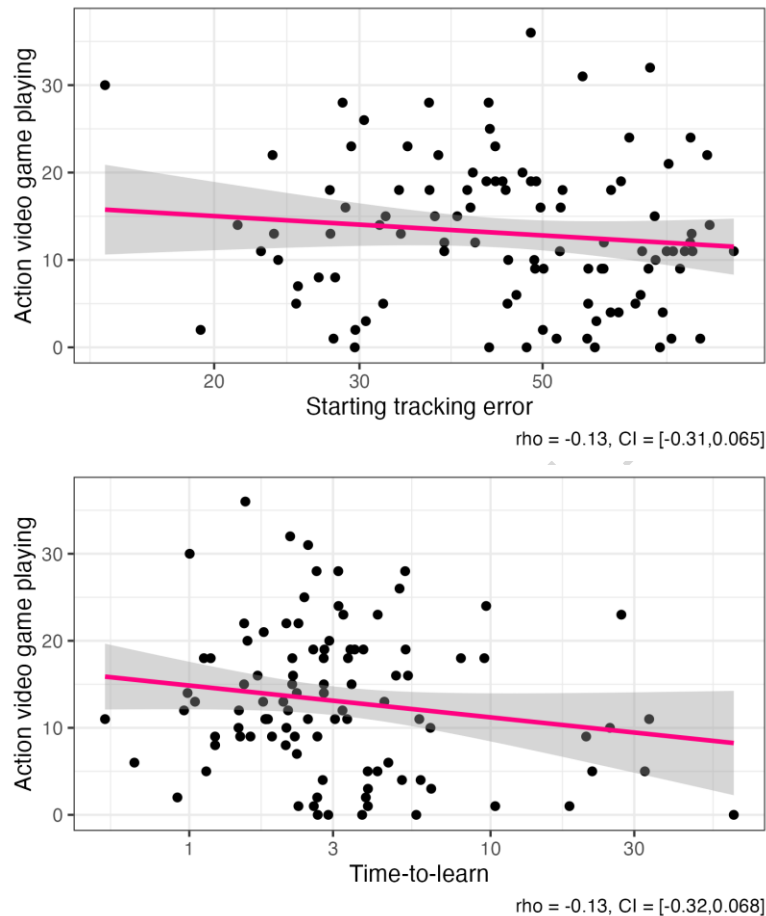


Figure 7. Rank correlations between learning and action video game playing in naive participants ($n = 100$). Similar and non-reliable correlations were observed between action video game playing and starting tracking error (top panel) and time to learn (bottom panel). Linear trends and 95% CI overlaid for demonstration purposes.

Concerning flight simulator experience, we observed no link between self-reported flight experience and either initial performance ($\rho = 0.02$, $CI_{95} = [-.18, .22]$) or time-to-learn ($\rho = -0.07$, $CI_{95} = [-.26, .13]$) on the tracking tasks (Figure 8).

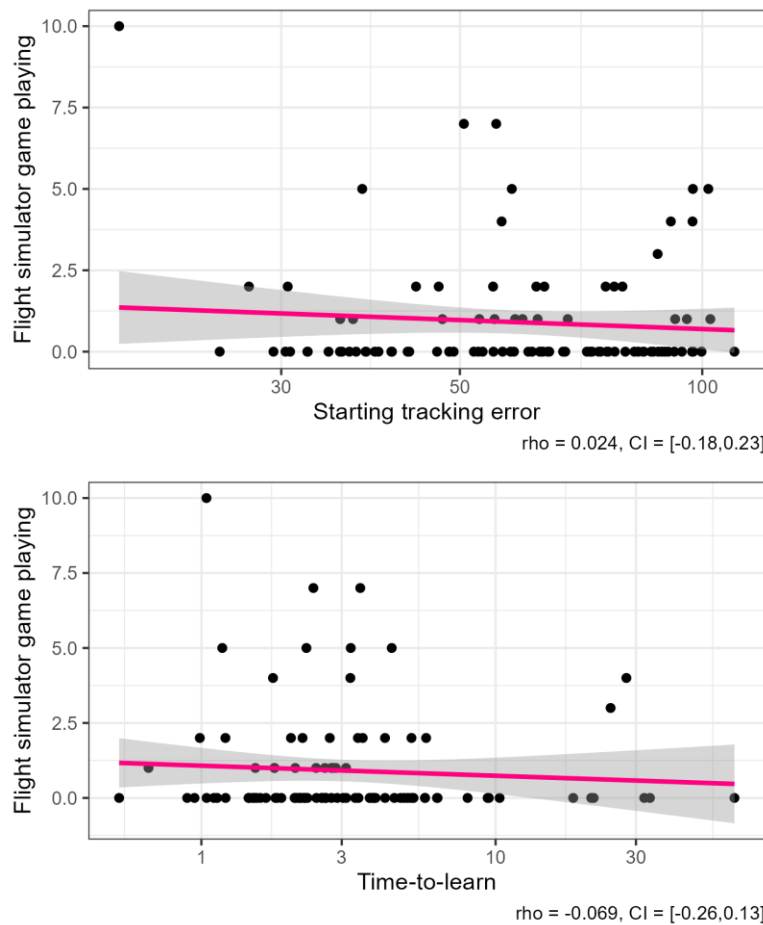


Figure 8. Rank correlations between learning and action flight simulator game playing in naive participants ($n = 100$). No reliable correlation was observed between flight simulator game playing and starting tracking error (top panel) or time to learn (bottom panel). Linear trends and 95% CI overlaid for demonstration purposes.

Discussion

Here we examined the extent to which learning on an occupationally-relevant visuo-motor tracking task was related to action video game play. More specifically, we examined both whether action video game play was associated with immediate differences in performance (i.e., from the very earliest moments) and/or with differences in learning through time. This is critical, as analyses of such tasks typically do not consider learning. Instead, it is more typical for single dependent variables for each subtask to be calculated by aggregating over measurements. We have recently argued that for many (if not most) tasks used in perceptual, cognitive, and motor psychology, such aggregation-based analyses are not appropriate (Cochrane et al., 2023, 2024; Cochrane & Green, 2021b; Kattner et al., 2017). Indeed, at the theoretical level, aggregated analyses inherently assume that performance across all timepoints is identically and independently distributed; in other words, that early behavior in the task is generated via the exact same process as late behavior in the task. This is unlikely to be true given how effectively

human beings learn. Furthermore, empirical results show that modeling even very short “measurement” tasks as changing through time provides both a better fit to the data and permits deeper inferences about the given behaviors (Clarke & Hunt, 2023; Cochrane et al., 2023, 2024; Cochrane & Green, 2021b; Gallistel et al., 2004; Kattner et al., 2017; Schmidt & Bjork, 1992). Although many have argued that the best way to characterize behavior is through the lens of learning, it is only recently, thanks to greater computational power, that trial-by-trial analyses of how performance progresses over time have become more common.

By including both a flight student group with some familiarity with the task as well as a naive group, our data further speaks to various stages of learning and how these may be affected by everyday activities such as video game training. According to the theory of Fitts and Posner (Fitts & Posner, 1967), for example, one would expect little impact of action video game experience on the very early cognitive stage of learning where the rules of the task have to be cognitively mastered. In contrast, one would expect greater impact of action video game experience once in the associative stage of learning during which participants become more at ease with the task (Bavelier et al., 2018).

Our results demonstrated, first and foremost, clear learning in each of our groups of participants and in each of the four tracking subtasks considered. Learning was notable despite quite large variability in learning curves across groups as well as within groups (see Figure 2). Consistent with their lesser familiarity with the task, our naive group showed greater starting tracking error than the flight student group. The two groups did not show a significant difference in learning rate (with on average each group getting halfway from start to asymptote in about 3.2 blocks). Finally, the flight student group was estimated to achieve better asymptotic performance than the student group. This latter finding is not surprising, given the flight students represented a selected sample of individuals expected to have an aptitude for the skills and abilities represented in the subtasks of the PBM battery.

When it came to the relationship between action video game experience and learning, both starting tracking error and time-to-learn correlated significantly with action video game play experience in flight students ($\rho = -.31$, $\rho = -.35$, respectively). Surprisingly, the learning indices showed less marked correlations with flight simulator game play experience. Starting tracking error did correlate with flight simulator game play ($\rho = -.21$), but time-to-learn did not ($\rho = -.09$). This finding warrants further exploration, especially given the fast pace of flight training that requires flight students to learn quickly, as well as the Navy’s recommendation that it may be useful to “practice using flight simulator software with a stick-and-throttle set” in preparing for the PBM subtest (NAMI, 2025). Perhaps encouraging action video game play may also be warranted, given that this finding supports the view that action video game play fosters the future learning of tasks that are not directly related to such game play. Finally, and crucially given our initial question, both starting tracking error and time-to-learn related to action video

game play in flight students, which suggests the possibility of both direct transfer and faster learning rate.

In contrast to the flight student population, neither action video game play nor flight simulator game play correlated with the initial tracking performance or learning measures in naive participants. This was the case despite the two groups showing very similar distributions of time-to-learn. On the one hand, this may signal that action video game play may only relate to learning in its intermediate stages after sufficient familiarity has been gained at the task. On the other hand, it may also result from greater sources of variability affecting naive participants' performance as compared to the flight students. Such variability may, for example, arise due to lower motivation among the naive (enlisted) sample compared to the flight students, for whom the PBM battery was relevant to their military occupation and used for selection. Naive participants may also be more variable in their performance, as suggested by Figure 2, especially in their starting tracking error. This may be due to various idiosyncratic differences in experience more heavily contributing to their performance on the task as compared to flight students, who had all already been exposed to previous official selection testing and unofficial practice materials obtained prior to testing. This would place flight students at an intermediate level of learning where performance is seen to be less noisy, while placing naive participants at an earlier, and noisier, level of performance.

The lack of correlation between our learning outcomes and flight simulator game play in the naive participants is expected given the very low level of reported flight simulator play in the naive group. Indeed, both correlations were quite low and clearly centered on zero. This was not the case for the action video game correlations, which despite being non-significant, showed the same basic patterns (i.e., toward better starting performance and faster learning as action video game experience grows) as was seen in the flight student group.

Limitations and Future Directions

The methodological constraints and limitations that inherently arise by performing work at the intersection of basic and applied science in turn leaves a host of open questions for future research. One such limitation is with regard to our participant sample, which consisted of 240 male participants and only 25 female participants. This imbalance, along with the overall low number of female participants, required that we analyze only male participants in the current work. While some previous literature suggests that females benefit as much (or in some cases more) than male participants from video game experience (Feng et al., 2007; Subrahmanyam & Greenfield, 1994), other research suggests the opposite (Powers et al., 2013). As such, whether the same pattern of results we found here in male participants would be found in female participants requires future examination. Furthermore, the naive sample comprised military personnel who were not selected through the same stringent screening process as the flight

students, which may introduce confounds related to baseline cognitive ability. Therefore, future research should examine how action gaming experience relates to cognitive ability and repeated PBM performance, or more generally, complex skill acquisition.

Next, there are a host of additional measures of individual backgrounds and experiences that could both speak to underlying mechanisms as well as potentially improve predictive models. For example, the video game survey that was utilized focused only on hours played by genre, leaving information about factors such as skill unmeasured. Because skill and experience are necessarily partially confounded, separate measures are necessary to pin down the nature of the effects (Large et al., 2019; Phillips & Green, 2024). There are also a host of other types of experience that could be useful predictors of performance on the task utilized here, from general computer experience (which could vary more widely in this population than, for instance, the university populations that make up the samples in much of the literature) through other cognitively and motorically demanding real-world experiences like certain sports (Mancı et al., 2023; Wang et al., 2013).

Similarly, here we measured performance on a reasonably short task that is known to be predictive of real-world behavior, but is not the real-world behavior itself. As such, it would be useful to know how long various effects last, that is, if one were to use video games to attempt to train performance on this task, how long would the effects remain (noting that the small amount of previous literature on this topic has seen benefits on the timescale of months to years; Feng et al., 2007; Li et al., 2009). Additionally important would be investigating whether non-gamers eventually “catch up” and if so how long that process takes. Furthermore, although there are known links between performance on the tracking task utilized here and flight training performance, and our work here shows links between action gaming and performance on the tracking task, this does not necessarily mean that a link would be found between action gaming and flight training performance (i.e., action gamers here could be good at the tracking task for a reason that does not underpin the task’s relation with flight training). As such, establishing the full causal chain will be necessary before any full applications can be considered.

Next, although the pattern of results seen here is more consistent with learning to learn than direct transfer, unpacking the exact mechanistic underpinnings of this learning to learn effect will require future research. Indeed, such learning-to-learn can arise via a number of different mechanics including improvements in cognitive skills that underpin successful learning (e.g., attentional control, cognitive and/or motor flexibility; Bavelier & Green, 2025) or various types of structure learning (Cochrane & Green, 2023; Kattner, Cochrane, Cox, et al., 2017). Given the nature of the tracking task, gaining a deeper understanding of the exact improvements that are resulting in augmented learning rates will be important.

Finally, while we have focused here on flight aptitude, as noted in the introduction, learning flexibility is at a premium in many 21st century occupations. In particular, while links between video game play and a host of other real-world tasks/occupations has been examined (from those more related to flight, such as unmanned aerial vehicles; Potdar & Dattel, 2024; to those far afield from flight, such as laparoscopic surgery; Rosser et al., 2007; Schlickum et al., 2008, 2009), none have been differentiated between direct transfer and learning to learn. In particular, although here we have focused on benefits of action video game playing, knowing whether any occupations might be harmed by such play would be of foremost importance (West et al., 2020).

Conclusion

In all, this study provides an additional demonstration that action video game play experience is linked with enhanced performance on tasks that, on the surface, are not directly related to action video games (or at a minimum are far more different than tasks between which no such generalization is seen in the perceptual and cognitive literature; i.e., vertical lines and horizontal lines). We see that it may do so both through direct transfer (better initial performance), as well as through learning-to-learn (faster learning rate). That this effect was only detected in flight students but not naive participants, despite both groups showing similar action video game play distributions (Cohen's $d = .23$, $CI_{95} [-.02, .47]$), points to other sources of variability being a greater contributor to learning behavior. More or less experience on the very task we measure learning on, early in the learning phase, would indeed be expected to overshadow any contribution of action video game play. It will be important in future studies to further evaluate when action video game play experience may best predict learning.

Data availability statement

Data may be made available by contacting Ciara Sibley, at Naval Research Laboratory (Ciara.m.sibley.civ@us.navy.mil), and initiating a data sharing request. Data to reproduce figures is available at doi.org/10.17605/OSF.IO/KAX7R.

Code availability statement

Code availability statement: Analysis code is available at doi.org/10.17605/OSF.IO/KAX7R (note that this file contains both analysis code and data).

Author Contributions

A.C.: Conceptualization, Formal analysis, Visualization, Writing - Original Draft

C.S.: Conceptualization, Methodology, Data Curation, Project Administration, Funding Acquisition, Writing — Review & Editing

R.N.: Resources, Supervision, Project Administration, Writing — Review & Editing

C.S.G.: Conceptualization, Funding Acquisition, Writing — Review & Editing

D.B.: Conceptualization, Writing — Review & Editing

References

- Amdurer, E., Boyatzis, R. E., Saatcioglu, A., Smith, M. L., & Taylor, S. N. (2014). Long term impact of emotional, social and cognitive intelligence competencies and GMAT on career and life satisfaction and career success. *Frontiers in Psychology*, 5. <https://doi.org/10.3389/fpsyg.2014.01447>
- Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn?: A taxonomy for far transfer. *Psychological Bulletin*, 128(4), 612–637. <https://doi.org/10.1037//0033-2909.128.4.612>
- Bavelier, D. (2022). *Bavelier Lab Video Game Questionnaire*. University of Geneva Brain & Learning Lab. www.unige.ch/fapse/brainlearning/vgq/
- Bavelier, D., Achtman, R. L., Mani, M., & Föcker, J. (2012). Neural bases of selective attention in action video game players. *Vision Research*, 61, 132–143. <https://doi.org/10.1016/j.visres.2011.08.007>
- Bavelier, D., & Green, C. S. (2025). Learning and Transfer: A Perspective From Action Video Game Play. *Current Directions in Psychological Science*, 34(1), 43–50. <https://doi.org/10.1177/09637214241287171>
- Bediou, B., Adams, D. M., Mayer, R. E., Tipton, E., Green, C. S., & Bavelier, D. (2018). Meta-analysis of action video game impact on perceptual, attentional, and cognitive skills. *Psychological Bulletin*, 144(1), 77–110. <https://doi.org/10.1037/bul0000130>
- Bediou, B., Rodgers, M. A., Tipton, E., Mayer, R. E., Green, C. S., & Bavelier, D. (2023). Effects of action video game play on cognitive skills: A meta-analysis. *Technology, Mind, and Behavior*, 4(1). <https://doi.org/10.1037/tmb0000102>
- Bejjanki, V. R., Zhang, R., Li, R., Pouget, A., Green, C. S., Lu, Z.-L., & Bavelier, D. (2014). Action video game play facilitates the development of better perceptual templates.

- Proceedings of the National Academy of Sciences*, 111(47), 16961–16966.
<https://doi.org/10.1073/pnas.1417056111>
- Bertua, C., Anderson, N., & Salgado, J. F. (2005). The predictive validity of cognitive ability tests: A UK meta-analysis. *Journal of Occupational and Organizational Psychology*, 78(3), 387–409. <https://doi.org/10.1348/096317905X26994>
- Binet, A., & Simon, Th. (1916). The development of intelligence in the child. (E. S. Kite, Trans.). In A. Binet & Th. Simon, *The development of intelligence in children (The Binet-Simon Scale)*. (pp. 182–273). Williams & Wilkins Co.
<http://content.apa.org/books/11069-004>
- Bürkner, P.-C. (2017). **brms**: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software*, 80(1). <https://doi.org/10.18637/jss.v080.i01>
- Carroll, J. B. (2004). *Human cognitive abilities: A survey of factor-analytic studies*. Cambridge University Press.
- Chisholm, J. D., Hickey, C., Theeuwes, J., & Kingstone, A. (2010). Reduced attentional capture in action video game players. *Attention, Perception, & Psychophysics*, 72(3), 667–671.
<https://doi.org/10.3758/APP.72.3.667>
- Clarke, A. D. F., & Hunt, A. R. (2025). Learn more from your data with asymptotic regression. *Journal of Experimental Psychology: General*. <https://doi.org/10.1037/xge0001710>
- Cochrane, A. (2020). TEfits: Nonlinear regression for time-evolving indices. *Journal of Open Source Software*, 5(52), 2535. <https://doi.org/10.21105/joss.02535>
- Cochrane, A., & Green, C. S. (2021). Assessing the functions underlying learning using by-trial and by-participant models: Evidence from two visual perceptual learning paradigms. *Journal of Vision*, 21(13), 5. <https://doi.org/10.1167/jov.21.13.5>

- Cochrane, A., & Green, C. S. (2023). Working memory is supported by learning to represent items as actions. *Attention, Perception, & Psychophysics*. <https://doi.org/10.3758/s13414-023-02654-z>
- Cochrane, A., Lu, Z.-L., & Green, C. S. (2024). Modeling Perceptual Learning as a Continuous Function of Time-on-Task Increases Theoretical Specificity and Statistical Power. *Journal of Cognitive Enhancement*. <https://doi.org/10.1007/s41465-024-00303-3>
- Cochrane, A., Sims, C. R., Bejjanki, V. R., Green, C. S., & Bavelier, D. (2023). Multiple timescales of learning indicated by changes in evidence-accumulation processes during perceptual decision-making. *NPJ Science of Learning*, 8(1), 19. <https://doi.org/10.1038/s41539-023-00168-9>
- Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, 64, 135–168. <https://doi.org/10.1146/annurev-psych-113011-143750>
- Donohue, S. E., Woldorff, M. G., & Mitroff, S. R. (2010). Video game players show more precise multisensory temporal processing abilities. *Attention, Perception, & Psychophysics*, 72(4), 1120–1129. <https://doi.org/10.3758/APP.72.4.1120>
- Dosher, B. A., & Lu, Z.-L. (2007). The Functional Form of Performance Improvements in Perceptual Learning: Learning Rates and Transfer. *Psychological Science*, 18(6), 531–539. <https://doi.org/10.1111/j.1467-9280.2007.01934.x>
- Draheim, C., Sibley, C., Herdener, N., Cochrane, A., Melick, S., Strong, K., & Coyne, J. (2025). *High Stakes Psychomotor Ability Assessment: A Military Selection Case Study of Practice Effects in Airplane Tracking Tasks*.

- Dye, M. W. G., Green, C. S., & Bavelier, D. (2009). The development of attention skills in action video game players. *Neuropsychologia*, 47(8–9), 1780–1789.
<https://doi.org/10.1016/j.neuropsychologia.2009.02.002>
- Fahle, M. (2004). Perceptual learning: A case for early selection. *Journal of Vision*, 4(10), 879–890. <https://doi.org/10.1167/4.10.4>
- Feng, J., Spence, I., & Pratt, J. (2007). Playing an action video game reduces gender differences in spatial cognition. *Psychological Science*, 18(10), 850–855.
<https://doi.org/10.1111/j.1467-9280.2007.01990.x>
- Gao, Y.-Y., Fang, Z., Zhou, Q., & Zhang, R.-Y. (2024). Enhanced “learning to learn” through a hierarchical dual-learning system: The case of action video game players. *BMC Psychology*, 12(1), 460. <https://doi.org/10.1186/s40359-024-01952-x>
- Gozli, D. G., Bavelier, D., & Pratt, J. (2014). The effect of action video game playing on sensorimotor learning: Evidence from a movement tracking task. *Human Movement Science*, 38, 152–162. <https://doi.org/10.1016/j.humov.2014.09.004>
- Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature*, 423(6939), 534–537. <https://doi.org/10.1038/nature01647>
- Green, C. S., & Bavelier, D. (2006). Enumeration versus multiple object tracking: The case of action video game players. *Cognition*, 101(1), 217–245.
<https://doi.org/10.1016/j.cognition.2005.10.004>
- Green, C. S., & Bavelier, D. (2007). Action-Video-Game Experience Alters the Spatial Resolution of Vision. *Psychological Science*, 18(1), 88–94.
<https://doi.org/10.1111/j.1467-9280.2007.01853.x>

- Green, C. S., Pouget, A., & Bavelier, D. (2010). Improved Probabilistic Inference as a General Learning Mechanism with Action Video Games. *Current Biology*, 20(17), 1573–1579. <https://doi.org/10.1016/j.cub.2010.07.040>
- Heathcote, A., Brown, S., & Mewhort, D. J. (2000). The power law repealed: The case for an exponential law of practice. *Psychonomic Bulletin & Review*, 7(2), 185–207.
- Hubert-Wallander, B., Green, C. S., & Bavelier, D. (2011). Stretching the limits of visual attention: The case of action video games. *WIREs Cognitive Science*, 2(2), 222–230. <https://doi.org/10.1002/wcs.116>
- Kattner, F., Cochrane, A., Cox, C. R., Gorman, T. E., & Green, C. S. (2017). Perceptual Learning Generalization from Sequential Perceptual Training as a Change in Learning Rate. *Current Biology*, 27(6), 840–846. <https://doi.org/10.1016/j.cub.2017.01.046>
- Kattner, F., Cochrane, A., & Green, C. S. (2017). Trial-dependent psychometric functions accounting for perceptual learning in 2-AFC discrimination tasks. *Journal of Vision*, 17(11), 3. <https://doi.org/10.1167/17.11.3>
- Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2004). Academic Performance, Career Potential, Creativity, and Job Performance: Can One Construct Predict Them All? *Journal of Personality and Social Psychology*, 86(1), 148–161. <https://doi.org/10.1037/0022-3514.86.1.148>
- Large, A. M., Bediou, B., Cekic, S., Hart, Y., Bavelier, D., & Green, C. S. (2019). Cognitive and Behavioral Correlates of Achievement in a Complex Multi-Player Video Game. *Media and Communication*, 7(4), 198–212. <https://doi.org/10.17645/mac.v7i4.2314>

- Mancı, E., Günay, E., Güdücü, Ç., Herold, F., & Bediz, C. Ş. (2023). The Effect of the Playing Positions in Basketball on Measures of Cognitive Performance. *Journal of Cognitive Enhancement*, 7(3–4), 230–241. <https://doi.org/10.1007/s41465-023-00269-8>
- Maniglia, M., & Seitz, A. R. (2018). Towards a whole brain model of Perceptual Learning. *Current Opinion in Behavioral Sciences*, 20, 47–55. <https://doi.org/10.1016/j.cobeha.2017.10.004>
- Mashburn, C. A., Burgoyne, A. P., & Engle, R. W. (2023). Working memory, intelligence, and life success: Examining relations to academic achievement, job performance, physical health, mortality, and psychological well-being. In R. Logie, N. Cowan, S. Gathercole, R. Engle, & Z. Wen (Eds.), *Memory in Science for Society* (1st ed., pp. 149–184). Oxford University PressOxford. <https://doi.org/10.1093/oso/9780192849069.003.0007>
- McKinley, R. A., McIntire, L. K., & Funke, M. A. (2011). Operator Selection for Unmanned Aerial Systems: Comparing Video Game Players and Pilots. *Aviation, Space, and Environmental Medicine*, 82(6), 635–642. <https://doi.org/10.3357/ASEM.2958.2011>
- NAMI, N. A. M. I. (2024). *ASTB FAQ*. www.med.navy.mil/Navy-Medicine-Operational-Training-Command/Naval-Aerospace-Medical-Institute/ASTB-FAQ/
- Ou, Y., McGlone, E. R., Camm, C. F., & Khan, O. A. (2013). Does playing video games improve laparoscopic skills? *International Journal of Surgery*, 11(5), 365–369. <https://doi.org/10.1016/j.ijsu.2013.02.020>
- Pasqualotto, A., Altarelli, I., De Angeli, A., Menestrina, Z., Bavelier, D., & Venuti, P. (2022). Enhancing reading skills through a video game mixing action mechanics and cognitive training. *Nature Human Behaviour*, 6(4), 545–554. <https://doi.org/10.1038/s41562-021-01254-x>

- Perkins, N., & Salomon, G. (1992). Transfer of Learning. In T. Husen & T. N. Postlewaite (Eds.), *The International Encyclopedia of Education* (2nd ed., pp. 425–441). Pergamon.
- Peters, J. L., Crewther, S. G., Murphy, M. J., & Bavin, E. L. (2021). Action video game training improves text reading accuracy, rate and comprehension in children with dyslexia: A randomized controlled trial. *Scientific Reports*, *11*(1), 18584.
<https://doi.org/10.1038/s41598-021-98146-x>
- Phillips, N., & Green, C. S. (2024). Associations between cognitive performance and extreme expertise in different competitive eSports. *Journal of Expertise*, *6*(4).
- Potdar, R., & Dattel, A. R. (2024). The Transferability of Pilots' Video Gaming Experience to the Skills and Situation Awareness of Operating UAVs. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *68*(1), 1808–1813.
<https://doi.org/10.1177/10711813241260300>
- Powers, K. L., Brooks, P. J., Aldrich, N. J., Palladino, M. A., & Alfieri, L. (2013). Effects of video-game play on information processing: A meta-analytic investigation. *Psychonomic Bulletin & Review*, *20*(6), 1055–1079. <https://doi.org/10.3758/s13423-013-0418-z>
- Puccio, G., Gazzì, G., Bertoni, S., Franceschini, S., Mancarella, M., Gori, S., Ronconi, L., & Facchetti, A. (2024). Action Video Games Training in Children with Developmental Dyslexia: A Meta-Analysis. *International Journal of Human–Computer Interaction*, *40*(22), 6829–6844. <https://doi.org/10.1080/10447318.2023.2267297>
- Rohde, T. E., & Thompson, L. A. (2007). Predicting academic achievement with cognitive ability. *Intelligence*, *35*(1), 83–92. <https://doi.org/10.1016/j.intell.2006.05.004>
- Rosser, J. C., Lynch, P. J., Cuddihy, L., Gentile, D. A., Klonsky, J., & Merrell, R. (2007). The impact of video games on training surgeons in the 21st century. *Archives of Surgery*

(Chicago, Ill.: 1960), 142(2), 181–186; discussion 186.

<https://doi.org/10.1001/archsurg.142.2.181>

Sala, G., Tatlidil, K. S., & Gobet, F. (2018). Video game training does not enhance cognitive ability: A comprehensive meta-analytic investigation. *Psychological Bulletin*, 144(2), 111–139. <https://doi.org/10.1037/bul0000139>

Schlickum, M. K., Hedman, L., Enochsson, L., Kjellin, A., & Felländer-Tsai, L. (2008). Transfer of systematic computer game training in surgical novices on performance in virtual reality image guided surgical simulators. *Studies in Health Technology and Informatics*, 132, 210–215.

Schlickum, M. K., Hedman, L., Enochsson, L., Kjellin, A., & Felländer-Tsai, L. (2009). Systematic Video Game Training in Surgical Novices Improves Performance in Virtual Reality Endoscopic Surgical Simulators: A Prospective Randomized Study. *World Journal of Surgery*, 33(11), 2360–2367. <https://doi.org/10.1007/s00268-009-0151-y>

Sharpe, B. T., Blacker, S. D., Myers, S. D., Birch, P. D. J., Poulus, D. R., & Vine, C. A. J. (2025). Commentary on the Transferability of Esports to Military and Emergency Responder Roles. *Journal of Electronic Gaming and Esports*, 3(1), jege.2025-0009. <https://doi.org/10.1123/jege.2025-0009>

Sibley, C. (2024). *High-Stakes Testing and Second Chances: From Data to Models* (Order No. 31242034) [Doctoral Dissertation, George Mason University]. Available from ProQuest Dissertations & Theses Global; Publicly Available Content Database. (3090764246). www.proquest.com/dissertations-theses/high-stakes-testing-second-chances-data-models/docview/3090764246/se-2

- Snell, N., Kattner, F., Rokers, B., & Green, C. S. (2015). Orientation Transfer in Vernier and Stereoacuity Training. *PLOS ONE*, *10*(12), e0145770.
<https://doi.org/10.1371/journal.pone.0145770>
- Strobach, T., Frensch, P. A., & Schubert, T. (2012). Video game practice optimizes executive control skills in dual-task and task switching situations. *Acta Psychologica*, *140*(1), 13–24. <https://doi.org/10.1016/j.actpsy.2012.02.001>
- Subrahmanyam, K., & Greenfield, P. M. (1994). Effect of video game practice on spatial skills in girls and boys. *Journal of Applied Developmental Psychology*, *15*(1), 13–32.
[https://doi.org/10.1016/0193-3973\(94\)90004-3](https://doi.org/10.1016/0193-3973(94)90004-3)
- Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, *27*(5), 1413–1432.
<https://doi.org/10.1007/s11222-016-9696-4>
- Walker, P. B., Olde, B. A., & Tatana M. Olson. (2007). *Improving Aviator Selection Using the Performance-Based Measurement Battery (PBMB)*.
<https://doi.org/10.13140/2.1.4073.2164>
- Wang, C.-H., Chang, C.-C., Liang, Y.-M., Shih, C.-M., Chiu, W.-S., Tseng, P., Hung, D. L., Tzeng, O. J. L., Muggleton, N. G., & Juan, C.-H. (2013). Open vs. Closed skill sports and the modulation of inhibitory control. *PloS One*, *8*(2), e55773.
<https://doi.org/10.1371/journal.pone.0055773>
- West, R., Swing, E. L., Anderson, C. A., & Prot, S. (2020). The Contrasting Effects of an Action Video Game on Visuo-Spatial Processing and Proactive Cognitive Control. *International Journal of Environmental Research and Public Health*, *17*(14), 5160.
<https://doi.org/10.3390/ijerph17145160>

Zhang, R.-Y., Chopin, A., Shibata, K., Lu, Z.-L., Jaeggi, S. M., Buschkuhl, M., Green, C. S., & Bavelier, D. (2021). Action video game play facilitates “learning to learn.” *Communications Biology*, 4(1), 1154. <https://doi.org/10.1038/s42003-021-02652-7>

ARTICLE IN PRESS

Conflict of Interest Statement

The authors declare no competing interests.

Acknowledgements

The current work was supported by internal funding from the U.S. Naval Research Laboratory. The work was partially supported by the Office of Naval Research Awards N00014-22-12283 to C.S.G and N00014-20-1-2074 & N00014-22-1-2559 to DB. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

ARTICLE IN PRESS

Iterative PBM Subtask	Phase	Time to complete
Dichotic Listening (DLT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	120 seconds
Vertical Tracking (VTT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	60 seconds
2-dimensional Airplane Tracking (ATT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	60 seconds
Two-Handed Tracking (ATTVTT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	120 seconds
Two-Handed Tracking + Dichotic Listening (ATTVTDLT)	Instructions	Self-paced
	Practice	30 seconds
	Scored	180 seconds
Two-Handed Tracking + Emergency Scenario (ATTVTTSN)	Instructions	Self-paced
	Scored	120 seconds

Editor Summary:

Occupational training is a core aspect of many careers, and relevant assessments are a necessity. Here, among flight students in the US Navy, it is shown that experience playing action video games is linked to screening assessments for flight training.

Peer Review Information:

Communications Psychology thanks Benjamin T. Sharpe, Florian Jentsch and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Primary Handling Editor: Jennifer Bellingtier available.