How do visual skills relate to action video game performance?

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It has been claimed that video gamers possess increased perceptual and cognitive skills compared to non-video gamers. Here, we examined to which extent gaming performance in CS:GO (Counter-Strike: Global Offensive) correlates with visual performance. We tested 94 players ranging from beginners to experts with a battery of visual paradigms, such as visual acuity and contrast detection. In addition, we assessed performance in specific gaming skills, such as shooting and tracking, and administered personality traits. All measures together explained about 70% of the variance of the players' rank. In particular, regression models showed that a few visual abilities, such as visual acuity in the periphery and the susceptibility to the Honeycomb illusion, were strongly associated with the players' rank. Although the causality of the effect remains unknown, our results show that high-rank players perform better in certain visual skills compared to low-rank players.

Introduction

Basic visual skills, such as contrast detection and orientation discrimination, are the building blocks for visual processing. It has been suggested that playing video games is associated with better performance in these basic perceptual abilities (for reviews, see

Bavelier, Shawn Green, Pouget, & Schrater, 2012; Bediou, Adams, Mayer, Tipton, Shawn Green, & Bavelier, 2018; Boot, Blakely, & Simons, 2011; Chopin, Bediou, & Bavelier, 2019). For example, Hutchinson and Stocks (2013) observed that action video game (i.e., a subset of video games, which rely on physical challenges such as hand-eye coordination and reaction time) players (AVGPs) performed better in a random-dot kinematograms task compared to non-video game players (NVGPs). This suggests that AVGPs are better at global motion detection. Likewise, AVGPs were observed to have improved perceptual speed (Dye, Green, & Bavelier, 2009) in the Test of Variables of Attention compared to NVGPs, whereas the speed-accuracy tradeoff was similar in both groups. Li, Polat, Scalzo, and Bavelier (2010) trained participants with video games to establish the causal effect of action gaming on temporal dynamics and observed reduced backward masking performance (i.e., reduced threshold elevation in a masked contrast detection task) in video game players (VGPs) compared to NVGPs. In addition, VGPs outperformed NVGPs in other perceptual skills, such as multiple object tracking (Green & Bavelier, 2006), task-switching (Shawn Green et al., 2012), spatial resolution (Green & Bavelier, 2007), and contrast sensitivity (Li, Polat, Makous, & Bavelier, 2009). These studies were either intervention studies (e.g., Li et al., 2010), that is, participants were trained with a specific video game, or cross-sectional (e.g., Hutchinson & Stocks, 2013).

Studies have also examined the benefits of playing video games on cognitive abilities (for reviews, see Bavelier et al., 2012; Bediou et al., 2018; Campbell, Toth, Moran, Kowal, & Exton, 2018; Spence & Feng, 2010). For example, VGPs showed enhanced change detection performance compared to NVGPs (Clark, Fleck, & Mitroff, 2011). Kowal, Toth, Exton, & Campbell (2018) tested AVGPs and NVGPs with a Stroop test, which tests inhibition, and a Trail-Making test (TMT), which measures processing speed and task-switching abilities. In both tasks, AVGPs showed faster reaction times compared to NVGPs. However, AVGPs made significantly more errors in the Stroop test compared to NVGPs (no significant difference in the TMT), which indicates that inhibitive abilities may be boosted at the expense of a speed-accuracy tradeoff.

Perceptual learning studies have often reported dramatic improvements in perceptual sensitivity. For example, participants improved performance when trained with a bisection stimulus, i.e., they were able to discriminate smaller offsets after training (e.g., Aberg & Herzog, 2009; Grzeczkowski, Clarke, Francis, Mast, & Herzog, 2017; Grzeczkowski, Cretenoud, Mast, & Herzog, 2019). Video gamers may similarly be exposed to learning effects (see Shawn Green, Li, & Bavelier, 2010), resulting in substantial positive effects in both perceptual and cognitive skills (but see Ferguson,

2007). However, perceptual learning was shown to be specific to the orientation (Ball & Sekuler, 1987; Fahle & Morgan, 1996; Grzeczkowski, Cretenoud, Herzog, & Mast, 2017; Schoups, Vogels, & Orban, 1995; Spang, Grimsen, Herzog, & Fahle, 2010), contrast (Sowden, Rose, & Davies, 2002; Yu, Klein, & Levi, 2004), and motion direction (Ball & Sekuler, 1982; Ball & Sekuler, 1987) of the trained stimulus. Hence, learning does not generalize to untrained stimuli, except when using specific training procedures, such as double training (e.g., Xiao, Zhang, Wang, Klein, Levi, & Yu, 2008). Importantly, many aspects of vision, including video gaming, could strongly benefit from a generalization of perceptual learning (Fahle, 2005).

Most studies so far focused on only one—or very few—task(s), and thus it is unclear whether gaming performance is related to some specific skills or to a common factor. In the latter case, we expect to find strong correlations between gamers' performance in visual tasks. However, this prediction is in contrast with the weak evidence for a unique common factor for vision (e.g., Cappe, Clarke, Mohr, & Herzog, 2014; but see Bosten, Goodbourn, Bargary, Verhallen, Lawrance-Owen, Hogg, & Mollon, 2017; for reviews, see Mollon, Bosten, Peterzell, & Webster, 2017; Tulver, 2019). It seems that visual perception is highly multifactorial. For example, there were only weak correlations between the susceptibility to different illusions, whereas strong correlations exist between different variants of the same illusion, suggesting that there are illusion-specific factors (Cretenoud et al., 2019; Cretenoud, Francis, Herzog, 2020; Cretenoud, Grzeczkowski, Bertamini, & Herzog, 2020; Grzeczkowski et al., 2017). Similarly, there seems to be no unique common factor in eye movements (Bargary, Bosten, Goodbourn, Lawrance-Owen, Hogg, & Mollon, 2017), hue scaling (e.g., Emery, Volbrecht, Peterzell, & Webster, 2017), and contrast perception (Bosten & Mollon, 2010; Peterzell, 2016; Peterzell, Schefrin, Tregear, & Werner, 2000).

The popularity of electronic sports (esports), which are video games played at a competitive – sometimes professional – level, has exploded in the last decades with a growing interest in athletes' performance (e.g., Wagner, 2006). One of the leading esports is Counter-Strike: Global Offensive (CS:GO; e.g., Nazhif Rizani & Iida, 2018), a first-person shooter action video game (see Supplementary Figure S1), in which players are split into two groups, that is, terrorists and counterterrorists. Players are usually matched against other players with similar ranks.

Specific motor and cognitive abilities are required to play these video games. For example, flicking, that is, the motor coordination between the player's move and shooting via the computer mouse, is crucial to eliminate the players of the opposite team in first-person shooter video games. Because some of these aspects rely on
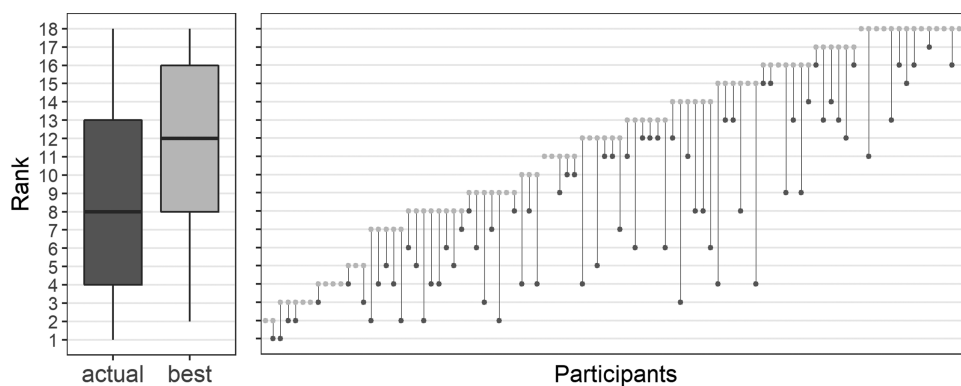
Figure 1. Actual (dark gray) and best (light gray) CS:GO ranks summarized in boxplots (left panel) and shown for each participant (right panel). The higher the rank, the better.

low-level visual skills (e.g., detecting an enemy strongly relies on vision and detection in the periphery), it is of interest to examine different aspects of the game and their relationship with different visual tasks.

To the best of our knowledge, all studies measuring visual abilities in VGPs compared performances between groups, that is, VGPs and NVGPs. However, there is no well-defined criterion to discriminate a VGP from a NVGP. For example, Hutchinson and Stocks (2013) considered participants who played video games for more than 10 hours per week as VGPs, whereas 5 hours per week during the last six months was sufficient in Green and Bavelier (2007). Here, we tested a broad range of CS:GO players, that is, from low- to high-rank players, with a battery of different visual tasks to examine what aspects are associated with expertise, and whether there is a unique, common factor underlying visual perception in AVGPs.

Materials and methods

Participants

Ninety-four participants were recruited (18–35 years; $M = 21.9$; $SD = 3.2$). All participants were AVGPs, played CS:GO at least once in the six months before the experiment, and had a CS:GO rank. Participants signed informed consent prior to the experiment and were paid 20 Swiss Francs per hour. Procedures were conducted in accordance with the Declaration of Helsinki, except for preregistration (§ 35), and were approved by the local ethics committee.

Procedure

The experiment consisted of four parts. First, participants answered a survey about their gaming

experience. Participants reported their actual CS:GO rank ($M = 9.0$, $SD = 5.2$; Figure 1), best CS:GO rank ever ($M = 11.8$, $SD = 4.9$; if "best" is not specified, we later refer to the actual ranks; Figure 1), the total ($M = 1232$, $SD = 1879$) and weekly ($M = 13.8$, $SD = 11.7$) number of hours they played CS:GO, and the average number of hours they sleep per night ($M = 7.7$, $SD = 1.1$). Note that ordinal ranks were converted to numerical equivalents from 1 to 18, with 18 being the highest rank (see Supplementary Table S1). Our sample spanned the entire range of ranks, that is, from beginners to experts.

Second, participants performed a battery of 12 visual paradigms: crowding (Crowd), contrast sensitivity (Contrast), the Honeycomb and Extinction illusions (HC/EX), a battery of other illusions (Illusions), N-back (NBack), orientation discrimination (Orient), random dot kinematograms (RDK), simple reaction times (ReacTime), pro- and anti-saccades (Saccade), Freiburg visual acuity (VisAcuity), visual backward masking (VBM), and visual search (VisSrch). The visual paradigms were presented in random order.

Additional variables were extracted for 6 of the 12 paradigms. For instance, the visual search paradigm was tested with two conditions, that is, with either four or 16 distractors. In total, we extracted 38 variables, which are listed in Table 1. When psychometric functions were used (Crowd, Contrast, Orient, RDK, VisAcuity, and VBM paradigms), we discarded blocks when the fit was invalid, i.e., when the point of subjective equality was outside of the search space, the goodness of fit <0.05, or the process did not converge (1.3% of values were discarded).

Third, gaming skills were assessed through six CS:GO mini-games, which were developed by Logitech (Lausanne, Switzerland) in collaboration with the University of Limerick (Ireland) and are publicly available on playmaster.gg. Playmaster is a training space for CS:GO that tests and compares gaming skills among the community and professionals. We extracted

Paradigm	Variable	Procedure	Lighting condition	Reliability	Feedback	Distance to screen (cm)	Nb of trials	Nb of training trials
Crowd	CrowdSize	PEST	dim	No	Negative	60	96	
	CrowdPeri						160	32
Contrast	Contrast	PEST	dim	No	Negative	200	80	
HC/EX	HC black	Adjustment	on	Yes	No	60	2	1
	HC white						2	
	EX black						2	1
	EX white						2	
Illusions	CS left	Adjustment	on	Yes	No	60	2	1
	CS right						2	
	EB small						2	1
	EB large						2	
	ML in						2	1
	ML out						2	
	PD left						2	1
	PD right						2	
	PZ down						2	1
	PZ up						2	
	TT left						2	1
	TT right						2	
	VH hor						2	1
	VH ver						2	
	WH left						2	1
	WH right						2	
	ZN left						2	1
	ZN right						2	
NBack	NBack		dim	No	Negative	60	40	10
Orient	Orient	PEST	dim	No	Negative	200	80	
RDK	RDK hor	QUEST	on	No	Negative	100	80	4
	RDK rad						80	4
ReacTime	ReacTime		dim	No	No	200	80	
Saccade	proTravel		on	No	Positive and negative	100	16	4
	proSac							
	antiTravel						16	4
	antiSac							
VisAcuity	VisAcuity	QUEST	dim	Yes	No	500	24	24
VBM	VBM	PEST	dim	Yes	Negative	200	80	
VisSrch	VisSrch4		dim	No	Negative	200	40	
	VisSrch16						40	

Table 1. Visual paradigms. Notes: Trials with response times longer than three seconds after the stimulus onset were replaced in the Crowd, Contrast, Orient, RDK, VBM, and VisSrch paradigms. In the Saccade paradigm, positive or negative feedback was provided at the end of each trial as a happy or sad smiley, respectively. In contrast, only negative auditory feedback was provided in the Crowd, Contrast, NBack, Orient, RDK, VBM, and VisSrch paradigms.

six gaming skills: flicking, holding, peeking, shooting, spraying, and tracking (see Supplementary Figure S1), as weighted sums of different features measured in the mini-games.

Fourth and last, participants answered seven self-report questionnaires, which were presented in random order: the Autism-Spectrum Quotient questionnaire (AQ; Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001), which consists of 50 items; a short version of the Liverpool Inventory of Feelings and Experiences questionnaire (O-LIFE; Mason, Linney, & Claridge, 2005), which investigates positive and negative schizotypy traits with 43 items; the short revised HEXACO personality inventory (HEXACO-60; Ashton & Lee, 2009), which measures 60 items of the six major dimensions of personality (HH:

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honesty-humility; EM: emotionality; EX: extraversion; AG: agreeableness; CO: conscientiousness; OP: openness to experience); the short version of the Barratt Impulsiveness Scale (BIS; Spinella, 2007), which measures impulsivity with 15 items; the Competitiveness Index (CI; Harris & Houston, 2010; Smither & Houston, 1992), which assesses competitive behavior with 14 items measured on a 5-point Likert scale; the Edinburgh handedness inventory (Oldfield, 1971), which assesses participants' hand dominance; and the Personality Research Form dominance subscale (PRFd; Jackson, 1974), which examines social dominance motivation with a 16-item true or false questionnaire. The AQ, BIS, CI, HEXACO, and O-LIFE questionnaires comprise several subscales. Participants could choose between English and French versions of the questionnaires.

Visual tasks and questionnaires were completed at EPFL individually in a quiet room. Because of technical issues, seven participants had to perform the gaming tasks in a gaming room at Logitech (Innovation Park, Switzerland), whereas the others performed the gaming tasks at EPFL. The experimenter stayed in the experimental (or gaming) room with the participant and answered questions at any time.

Apparatus

Stimuli were presented on a BenQ XL2540 LCD monitor (resolution of 1920 × 1080 pixels; screen size: 24.5″) with a refresh rate of 240 Hz. Gaming tasks were performed on an ASUS VG248QE monitor (resolution of 1920 × 1080 pixels; screen size: 24″) with a refresh rate of 144 Hz.

Visual paradigms

Table 1 summarizes details for each visual paradigm, such as the distance to the screen and the light conditions. Stimulus luminance varied between 1 cd/m^2 (black) and 98 cd/m^2 (white).

Crowding

Our paradigm was similar to the one used in Green and Bavelier (2007). First, an E optotype was shown in the periphery, while participants fixated a red dot in the center of the screen (Figure 2a). The red dot was presented for 250 ms. The E optotype was shown for 150 ms with a delay of 100 ms compared to the red dot and at an eccentricity of 10 arcdeg to the right of the red dot. Participants were asked to report the orientation of the optotype within 3 secs by using push buttons, i.e., either standard (right button) or mirrored (left button) orientation. Using an adaptive staircase

procedure (parameter estimation by sequential tracking PEST; starting value: 65 arcmin; range value: 10 to 200 arcmin; Taylor & Creelman, 1967), the stimulus size was varied to reach a threshold of 80% of correct responses (CrowdSize).

Second, the task was the same as before and two optotype distractors were added above and below the optotype target. The distractors were randomly oriented in one of the four cardinal directions, and the orientations were counterbalanced in a full factorial fashion. The size of the target was fixed according to the first part of the paradigm (i.e., CrowdSize) and the distance between the target and the distractors was manipulated using a PEST procedure (starting value: 200 arcmin; range value: 6 × CrowdSize to 300 arcmin) to reach 75% of correct responses (CrowdPeri).

Contrast sensitivity

Contrast sensitivity was measured with a 2IFC task (see Lahav, Levkovitch-Verbin, Belkin, Glovinsky, & Polat, 2011). A red fixation dot was presented in the middle of the screen, and subsequently a red and a green circles appeared (2 arcdeg in diameter). Participants indicated in which circle a Gabor patch was presented (spatial frequency: 4.0 cy/arcdeg; duration of presentation: 100 ms; envelope sigma: 0.30 arcdeg; Figure 2b) by pressing a red or green push button, respectively. The mean luminance was 50% and Gabors were rendered using dithering to increase gray level resolution. A PEST procedure (starting value: 10%) was used to measure the contrast threshold level at which participants reached 75% of correct responses.

Honeycomb and extinction illusions

This paradigm was based on a previous study by Bertamini, Herzog, and Bruno (2016; see also Bertamini, Cretenoud, & Herzog, 2019). The Honeycomb and Extinction illusions are characterized by an inability of the participants to see shapes (barbs in the case of the Honeycomb illusion; dots in the case of the Extinction illusion) in the periphery of a uniform texture. The background image (Figures 3a-d) filled the screen. While fixating a red central cross, participants adjusted the size of a red ellipse on the x and y axes using the computer mouse, so that all barbs (Honeycomb) or dots (Extinction) inside the ellipse were perceptible to them.

The red ellipse was displayed with a random size (within the screen size) at the beginning of each trial. Both illusions were tested with two contrast polarity conditions, that is, either black or white barbs in the Honeycomb illusion (Figures 3a-b) and either black or white dots in the Extinction illusion (Figures 3c-d). Hence, there were four conditions (HC black, HC white, EX black, EX white), and each condition was
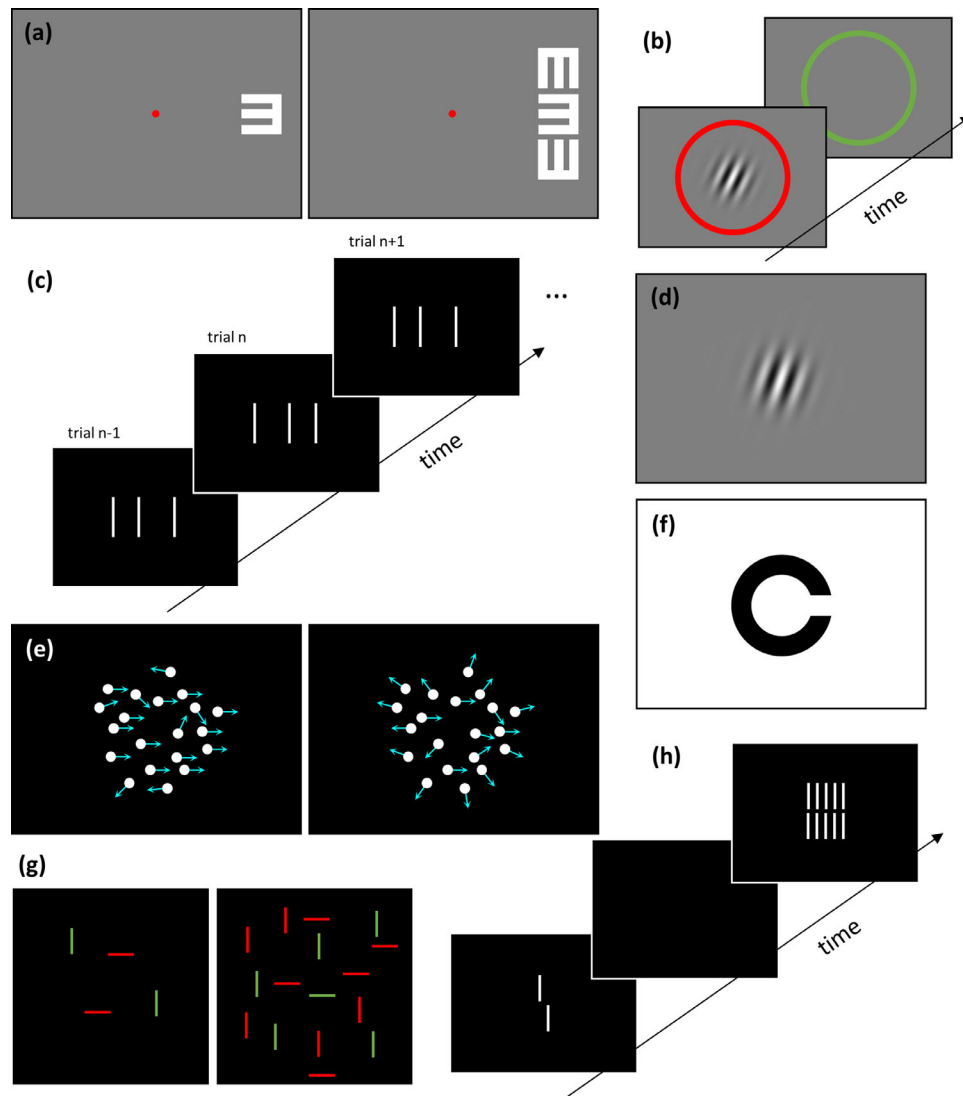
Figure 2. Schematic and exemplary representations of some of the visual paradigms tested. (a) Crowding: the size of the E optotype (left panel) and the distance between the target and distracting optotypes (right panel) varied according to a staircase procedure; (b) contrast sensitivity; (c) N-back with N = 1; (d) orientation discrimination; (e) horizontal (left panel) and radial (right panel) random dot kinematograms (cyan arrows indicate motion direction and were not part of the stimulus); (f) Freiburg visual acuity; (g) visual search (left panel: four-line condition; right panel: 16-line condition); (h) VBM with a five-element grating.

tested twice in a random order. There was no time limit for the adjustment. Random light and dark gray checkerboards (40 random masks presented for 0.5 second each and made of squares of 0.52 arcdeg in side with 0.35 and 0.65 of the maximum luminance) were shown after each trial to reduce the aftereffect. The extracted value was the area of the adjusted ellipse.

Illusions

A battery of nine other illusions was tested (Figures 3e-m): contrast (CS), Ebbinghaus (EB), Müller-Lyer (ML), Poggendorff (PD), Ponzo (PZ), Tilt (TT), vertical-horizontal (VH), White (WH), and

Zöllner (ZN). A method of adjustment was used to measure illusion susceptibility, that is, participants were asked to adjust the size (EB, ML, PZ, VH), shade of grey (CS, WH), orientation (TT, ZN), or position (PD) of an element to match the size, shade of grey, orientation, or position, respectively, of a reference on the screen by moving the computer mouse. The reference and adjustable elements were the inside squares in the CS illusion, the central disks in the EB illusion, the vertical segments with inward- and outward-pointing arrows in the ML illusion, the left and right parts of the interrupted diagonal in the PD illusion, the upper and lower horizontal segments in the PZ illusion, the small left and right Gabor patches
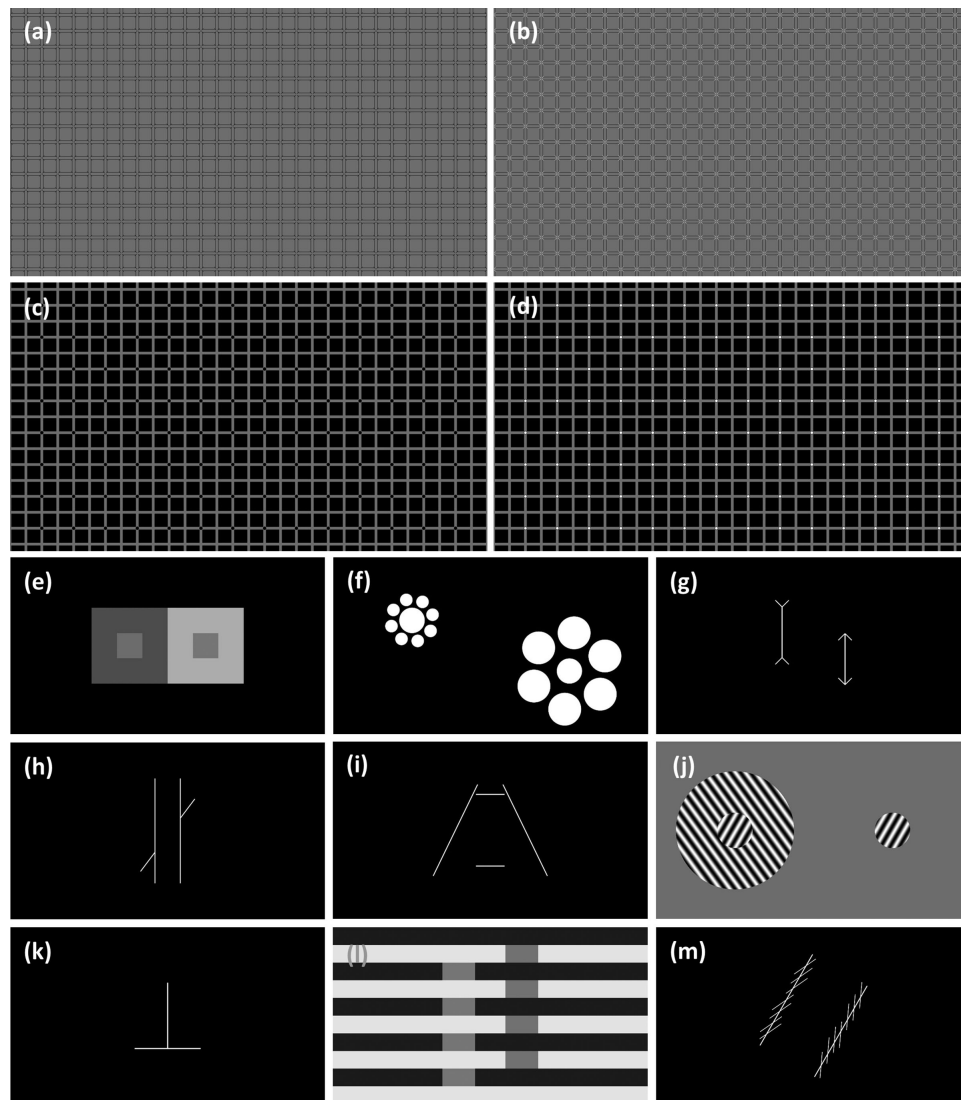
Figure 3. The Honeycomb illusion with (a) black (HC black) and (b) white (HC white) barbs and the Extinction illusion with (c) black (EX black) and (d) white (EX white) dots. The red adjustable ellipse and fixation cross are not depicted here. The images (a) to (d) need to be enlarged so as to fill a large proportion of the visual field; for details, see Bertamini et al. (2016). The battery of other illusions: (e) CS: contrast, (f) EB: Ebbinghaus, (g) ML: Müller-Lyer, (h) PD: Poggendorff, (i) PZ: Ponzo, (j) TT: Tilt, (k) VH: vertical-horizontal, (l) WH: White, and (m) ZN: Zöllner. Illusions (e) to (m) were all tested with two conditions. For example, the upper horizontal line of the Ponzo illusion was adjusted to match the length of the lower horizontal line, or inversely.

in the TT illusion, the horizontal and vertical segments in the VH illusion, the two columns of rectangles in the WH illusion, and the two main streams in the ZN illusion.

Each illusion was tested in two conditions: one element (or series of elements, in the case of the White illusion) was in turn the reference or the adjustable element. For example, in the Ebbinghaus illusion, the task was either to adjust the size of the left central disk so that it appeared to be the same size as the right central disk or to adjust the size of the right central disk so that it appeared to be the same size as the left central disk. The order of presentation of the different illusions and conditions was randomized across participants and

there was no time constraint. For a detailed description of the illusions, refer to Cretenoud et al. (2019) and Grzeczkowski et al. (2017). The extracted values were the illusion magnitudes expressed as a difference compared to the reference. Positive and negative illusion magnitudes indicate over- and under-adjustments, respectively.

N-back

We tested a one-back paradigm based on a bisection stimulus, which consists of three vertical lines with the central line being either offset to the left or right compared to the veridical center. The vertical lines were

1200 arcsec in length and the offset was fixed at 100 arcsec. Each trial consisted in a bisection stimulus, which was shown for 150 ms. Participants were asked to report whether the offset of the current stimulus was on the same or opposite side compared to the offset of the previous stimulus (one-back; Figure 2c) using two push buttons. Forty-one bisection stimuli were shown. We extracted the percentage of correct responses.

Orientation discrimination

Participants performed an adapted version of the orientation discrimination paradigm used in Tibber, Guedes, and Shepherd (2006). Each trial consisted in a red central dot followed by a Gabor patch (spatial frequency: 3.3 cy/arcdeg; duration of presentation: 100 ms; envelope sigma along orientation: 0.57 arcdeg; envelope sigma perpendicular to orientation: 0.19 arcdeg), which was centrally displayed (Figure 2d). Gabors were rendered using dithering to virtually increase gray level resolution. The mean luminance was 50% and the target contrast was 80%. Participants were asked to discriminate between clockwise and counterclockwise stimuli by using two push buttons. The Gabor orientation at which participants gave 75% of correct responses was estimated using a staircase PEST procedure (starting value: 5°).

Random dot kinematograms

The random dot kinematograms paradigm measures global motion perception (Edwards & Badcock, 1995; Hutchinson & Stocks, 2013; Newsome & Park, 1988). Two thousand dots were moving at 5 arcsec/s in a circular aperture (inner diameter: 1 arcdeg; outer diameter: 12 arcdeg) for 500 ms. Each trial consisted of a proportion of dots moving coherently while the rest of the dots moved independently (i.e., distractors; Figure 2e). Participants had to discriminate between leftward and rightward (horizontal, RDK hor) or inward and outward (radial, RDK rad) global motion by using two push buttons. The proportion of dots moving coherently was adapted using a staircase procedure (QUEST with the prior for coherence centered at 60% with SD 50%; Watson & Pelli, 1979; Watson & Pelli, 1983) to reach 75% of correct responses. The two conditions were tested sequentially, and the order was randomized across participants.

Simple reaction times

We used a modified version of the classic Hick-paradigm (Hick, 1952). Participants were instructed to press a mouse button as quickly as possible after a white square (3 arcdeg in side) appeared on a black background. To prevent participants from predicting when the white square appeared, the intertrial interval varied randomly (minimum: 1500 ms; maximum: 3500 ms). The extracted value was the median reaction time (outlier trials were removed using a modified z-score; Iglewicz & Hoaglin, 1993).

Prosaccades and antisaccades

Participants gazed at a fixation dot in the center of the screen and were asked to make a prosaccade or an antisaccade toward or away from a target, respectively. The color of the fixation dot, that is, green or red, indicated whether a prosaccade or antisaccade was required, respectively. The target was randomly displayed to the left or to the right of the fixation dot. A positive or negative feedback was provided at the end of each trial as a happy or sad smiley, respectively. Participants were positioned in the head rest of an SMI iViewXHi-Speed 1250 eye tracker (Sensomotoric Instruments, Teltow, Germany), and eye movements were recorded binocularly at 500 Hz. For both prosaccades and antisaccades, we extracted the median travel time (i.e., saccade duration; proTravel and antiTravel), and median saccade time (i.e., delay between the target onset and the saccade onset; proSac and antiSac). As in the simple reaction times paradigm, a modified z-score was used to detect and remove outlier trials.

Freiburg visual acuity

Visual acuity was measured following the procedure of the Freiburg visual acuity test (Bach, 1996). Participants were presented with Landolt-C optotypes (Figure 2f) with randomized gap orientations and were asked to indicate the direction of the gap ("up", "up-right", "right", "down-right", "down", "down-left", "left", or "up-left") using an eight-button controller. The size of the optotype was varied according to a staircase QUEST procedure, and we extracted the size corresponding to 75% of correct responses.

Visual backward masking

In a visual backward masking paradigm (Herzog, Kopmann, & Brand, 2004; Herzog & Koch, 2001; Roinishvili, Chkonia, Stroux, Brand, & Herzog, et al., 2011), a Vernier stimulus, which consists of two vertical bars offset in the horizontal direction, was presented for 10 ms. The offset between the two horizontal bars was fixed at 75 arcsec. The Vernier stimulus was followed by a variable interstimulus interval, that is, a blank screen, and by a grating for 300 ms (Figure 2h). The grating consisted of five aligned elements of the same length as the Vernier stimulus. Participants were asked to report the offset direction of the lower bar in the Vernier stimulus by using two push buttons. The interstimulus interval vas varied using a PEST procedure (starting

value: 190 ms) so that participants reached 75% of correct responses.

Visual search

In the visual search paradigm, four (VisSrch4) or 16 (VisSrch16) lines were presented randomly within a black square. Using two push buttons, participants had to report as quickly as possible whether a green horizontal line was present within an array of distractors (green vertical, red vertical, and horizontal lines; Figure 2g). The green horizontal line, that is, the target, was present in 50% of the trials. The median reaction time was extracted for correct trials in both conditions (after outlier trials were excluded according to modified *z*-scores).

Pre-processing and data analysis

Data were extracted in Matlab (MathWorks, Inc., Natick, MA, USA) and analyses were performed in R (R Core Team, 2018), except when mentioned. Alpha level for statistical significance was 0.05.

Reliability

We computed reliability estimates for the variables extracted from visual paradigms, which were tested twice, that is, the Honeycomb and Extinction illusions, the battery of other illusions, visual acuity, and visual backward masking. As suggested by Shrout and Fleiss (1979), two-way mixed effects models (intraclass correlations of type (3,1) or $ICC_{3,1}$) were computed. Most reliabilities were significant after Bonferroni correction was applied for multiple comparisons (Supplementary Table S2). However, Koo and Li (2016) suggested that ICC coefficients lower than 0.5 are indicative of poor reliability. Hence, variables with 95% confidence interval of the ICC coefficient including 0.5, i.e., the contrast, Ebbinghaus, Müller-Lyer, Ponzo, Tilt, vertical-horizontal, and White illusions, were not considered for further analysis (we excluded both conditions of an illusion even when only one condition showed poor reliability). Note that results were similar when including all variables.

Illusions

Only two illusions showed acceptable reliabilities, namely the Poggendorff and Zöllner illusions. The two conditions of the Poggendorff ($r = 0.721$, $p < 0.001$) and Zöllner ($r = -0.712$, $p < 0.001$) illusions were strongly correlated, suggesting stable individual differences across both conditions. Therefore the two conditions of each illusion were combined into a global

illusion magnitude, which was expressed as the sum of the absolute effects in the two conditions.

Bertamini, Cretenoud, and Herzog (2019) recently observed a dissociation between the Honeycomb and Extinction illusions depending on contrast polarity, suggesting that different mechanisms are operating in the black and white conditions of both illusions, respectively. Here, we computed a repeated-measures analysis of variance and similarly observed a significant interaction ($F[1,93] = 118.7$, $p < 0.001$; see Supplementary Figure S2) between the illusion type (Honeycomb or Extinction illusion) and contrast polarity (black or white). Therefore the two conditions of the Honeycomb and Extinction illusions were not combined into a global illusion magnitude.

Data transformation and outlier removal

The normality assumption was tested by computing a Shapiro-Wilk test for each variable. Some distributions violated the normality assumption (see Supplementary Table S3). Hence, each distribution was rescaled to approximate a normal distribution. First, we shifted the data distribution to positive values only. Second, we removed outliers based on modified *z*-scores, which are computed from the median and median absolute deviation rather than the mean and standard deviation, respectively, according to a 3.5 criterion (Iglewicz & Hoaglin, 1993). Third, we optimized the λ exponent of a Tukey power transformation (see Supplementary Table S3) to maximize normality according to the Shapiro-Wilk test. Fourth, including the previously removed outliers, data were transformed using the Tukey transformation with the optimized λ parameter. Fifth, we standardized the data by computing modified *z*-scores. Outliers were removed only in the visual variables. Last, we flipped the sign of visual variables when lower values indicated better performance (CrowdSize, CrowdPeri, Contrast, Poggendorff, Zöllner, Orient, RDK hor, RDK rad, ReacTtime, proTravel, proSac, antiTravel, antiSac, VBM, VisSrch4, and VisSrch16). Higher values indicate better performance in all gaming variables.

We imputed outlying and missing values using the "mice" function from the mice R package with method "norm" (Bayesian linear regression with 20 imputation samples) to compute factor analysis and regression models.

Questionnaires

To reduce the complexity of our dataset, the three subscales of the BIS (NI: nonplanning impulsivity, MI: motor impulsivity, AI: attentional impulsivity), which showed strong correlations with each other (NI-MI: $r = 0.441$, $p < 0.001$; NI-AI: $r = 0.406$, $p < 0.001$; MI-AI: $r = 0.532$, $p < 0.001$), were summed in a total score,

	CrowdSize	CrowdPeri	Contrast	HC black	HC white	EX black	EX white	Poggendorff	Zöllner	NBack	Orient	RDK hor	RDK rad	ReacTime	proTravel	proSac	antiTravel	antiSac	VisAcuity	VBM	VisSrch4	VisSrch16	Shoot	Spray	Track	Hold	Flick	Peek	NbHoursPerWeek	NbTotalHours	Actual CS:GO rank	Best CS:GO rank	NbHoursSleep
CrowdSize		.14	−.15	−.05	−.01	.08	.17	−.01	.21	.26	.02	.14	.14	.13	.17	.17	.04	.03	.16	.08	.09	.09	.04	.03	−.06	.24	.04	.06	−.05	−.13	.09	.03	−.17
CrowdPeri			.18	.11	−.01	.12	.34	.18	.04	−.03	−.06	−.09	−.04	.07	−.05	−.23	.04	−.17	.18	.07	.09	.03	.16	−.02	.21	.07	.24	.11	.04	.12	.06	−.02	−.08
Contrast				−.02	−.03	.06	.01	.19	.11	.04	.10	−.09	−.01	−.01	.05	.08	.02	.09	.33	.45	.06	−.01	−.09	−.02	−.05	.00	−.03	.06	−.10	.00	−.03	−.04	.21
HC black					.82	.70	.50	.06	.01	−.05	−.14	−.27	−.03	.10	.06	.19	.09	.10	−.11	−.03	.13	.25	.16	.08	−.03	.06	−.04	.08	.17	.17	.19	.15	−.03
HC white						.77	.53	.02	−.05	−.10	−.11	−.21	−.03	.06	.12	.20	.07	.09	−.10	−.07	.16	.30	.19	.09	−.02	.06	−.13	.09	.24	.23	.30	.22	.01
EX black							.57	.14	.10	−.01	−.08	−.18	−.09	.15	.01	.18	−.03	.03	−.03	.02	.17	.36	.12	.01	−.06	.13	−.11	.10	.05	.10	.09	.08	−.01
EX white								−.09	.04	.08	.07	−.06	−.07	.15	.13	.10	.18	.05	.15	.01	.17	.19	.25	.10	.27	.11	.19	.16	.12	.23	.28	.22	−.10
Poggendorff									.11	.09	.05	.03	.15	.14	.06	.14	.00	.12	.29	.14	−.09	.00	−.17	.03	−.07	.07	−.05	.02	.01	−.14	−.12	−.18	.09
Zöllner										.27	.20	−.03	.00	.06	.29	.06	.21	−.01	.16	.22	.07	.14	−.13	−.02	.04	−.06	.08	.05	−.19	−.29	−.25	−.23	−.12
NBack											.16	.04	−.04	.20	.09	.15	−.12	.19	.02	.33	.19	.10	−.10	−.03	−.04	.13	.06	.17	−.10	−.23	−.10	−.18	−.08
Orient												−.07	.11	.14	.11	−.05	.10	.20	.07	.21	.31	.15	.05	.24	.16	.06	.18	.04	.03	−.01	.09	.03	−.03
RDK hor													.42	.11	.04	.01	−.03	.08	.19	−.13	−.02	.03	.18	.19	.22	.09	.07	.01	.08	.12	.04	.11	−.06
RDK rad														.06	.15	.16	.07	.22	.23	.10	.04	.11	.11	.18	−.01	.15	.12	.10	−.05	.06	.09	.12	−.06
ReacTime															.20	.45	.08	.45	−.07	.21	.35	.35	.23	.07	.03	.34	.07	.03	.04	.14	.18	.18	−.09
proTravel																.26	.84	.22	.11	.19	.20	.20	.06	.18	.09	.07	.08	.12	.05	.12	.14	.18	.05
proSac																	−.03	.68	.04	.13	.29	.16	.14	.07	.00	.19	−.03	.09	.07	.17	.25	.16	.08
antiTravel																		−.03	.11	.09	.10	.15	.01	.19	.17	−.09	.13	.06	.09	.18	.12	.21	−.07
antiSac																			.08	.19	.34	.24	.07	.05	.08	.16	.08	.05	−.01	.14	.15	.07	.06
VisAcuity																				.39	−.11	−.04	−.02	−.01	.13	.02	−.14	.03	−.13	−.16	−.05	−.11	.02
VBM																					.12	.08	−.07	.00	.03	.14	.04	.04	−.10	−.08	−.01	−.05	.16
VisSrch4																						.79	.13	−.10	.11	.12	.06	−.09	.00	.20	.20	.19	−.16
VisSrch16																							.09	−.08	.03	.04	−.07	−.05	−.05	.13	.11	.17	−.20
Shoot																								.41	.54	.29	.30	.42	.36	.55	.63	.63	−.07
Spray																									.34	.10	.31	.19	.24	.41	.46	.45	−.11
Track																										.27	.40	.21	.20	.44	.51	.50	−.13
Hold																											.19	.29	.07	.12	.19	.17	−.07
Flick																												.11	.05	.35	.31	.33	−.01
Peek																													.05	.13	.17	.20	.08
NbHoursPerWeek																														.35	.34	.37	−.09
NbTotalHours																															.75	.84	−.07
Actual CS:GO rank																																.86	−.04
Best CS:GO rank																																	−.07

Table 2. Correlations between each pair of visual (green), gaming (orange), and CS:GO related (purple) variables expressed as correlation coefficients (Pearson's r). A color scale from blue to red shows the effect sizes from $r = -1$ to $r = 1$. Numbers in italics indicate significant results without correction ($\alpha = 0.05$) and bold numbers indicate significant results with Bonferroni correction ($\alpha = 0.05/990$). See Supplementary Table S4 for the correlations with other questionnaire variables.

which was considered for further analysis. Similarly, we summed the two subscales of the CI (EC: enjoyment of competition, CO: contentiousness) for further analysis, since they significantly correlated ($r = 0.314$, $p = 0.002$). Similarly, we later only considered the total score (i.e., we summed the subscales) of the AQ questionnaire (SS: social skills, AS: attention switch, AD: attention to detail, CO: communication, IM: imagination) and short version of the O-LIFE questionnaire (UE: unusual experiences, IA: introverted anhedonia, CD: cognitive disorganization, IN: impulsive nonconformity). However, the HEXACO personality inventory subscales were kept as separate variables because they showed weak intercorrelations (Table 2).

Results

Correlations

Correlations were computed between each pair of extracted variables (45 variables, 990 comparisons in total) and correlations between visual, gaming, and CS:GO related variables are reported in Table 2. For the sake of readability, correlations with other questionnaire variables (e.g., AQ, BIS, and O-LIFE) are reported in the Supplementary File (Supplementary Table S4). These correlations were weak and mostly nonsignificant ($M_r = -0.008$; $SD_r = 0.119$).

Similarly, correlations were in general weak between pairs of visual variables, except between pairs of variables that were extracted from the same paradigm, for example, between the two conditions of the visual search paradigm (VisSrch4-VisSrch16: $r = 0.790$, $p < 0.001$), and between the Honeycomb and Extinction variables (all ps < 0.001; HC black-HC white: $r = 0.819$; HC black-EX black: $r = 0.702$; HC black-EX white: $r = 0.501$; HC white-EX black: $r = 0.767$; HC white-EX white: $r = 0.527$; EX black-EX white: $r = 0.575$), as reported previously (Bertamini et al., 2019). Interestingly, performance in contrast detection and visual backward masking strongly correlated (Contrast-VBM: $r = 0.449$, $p < 0.001$), as previously observed in healthy young adults (da Cruz, Shaqiri, Roinishvili, Favrod, Chkonia, Brand, Figueiredo, & Herzog, 2020).

In contrast, gaming variables showed stronger intercorrelations ($M_r = 0.291$; $SD_r = 0.121$). Similarly, correlations between CS:GO related questionnaire variables (Actual CS:GO rank, Best CS:GO rank, NbHourPerWeek, NbTotalHours) and gaming variables were rather strong ($M_r = 0.314$; $SD_r = 0.182$), which was expected since expertise is gained

through training (for example, see Macnamara, Hambrick, & Oswald, 2014). For instance, the actual CS:GO rank strongly related to the total number of hours played (Actual CS:GO rank-NbTotalHours: $r = 0.748$, $p < 0.001$) but also to the gaming skills, such as the performance in the shooting mini-game (Actual CS:GO rank-Shoot: $r = 0.629$, $p < 0.001$).

Importantly, the actual CS:GO rank significantly correlated with some visual variables, namely with the Honeycomb white illusion (HC white: $r = 0.298$, $p = 0.004$), Extinction white illusion (EX white: $r = 0.278$, $p = 0.007$), Zöllner illusion ($r = -0.249$, $p = 0.016$), saccade time in pro-saccades (proSac: $r = 0.251$, $p = 0.015$), and with three personality traits (HEXACO HH: $r = 0.232$, $p = 0.024$; HEXACO OP: $r = -0.275$, $p = 0.007$; PRFd: $r = -0.254$, $p = 0.014$). However, not all of these correlations survived Bonferroni correction. Overall, correlations between pairs of visual variables were weak, while we observed stronger correlations between pairs of gaming related variables (including variables related to the rank and amount of training).

Exploratory factor analysis

In order to explore whether a strong and unique factor underlies vision in action video game players and to keep the participant/variable ratio as large as possible, only the visual variables (22 variables) were subjected to an exploratory factor analysis (EFA). The Kaiser-Meyer-Olkin test for sampling adequacy was computed to quantify the degree of intervariable correlations. Visual variables that showed an unacceptable measure of sampling adequacy (i.e., MSA < 0.5) were removed sequentially until all variables showed an acceptable MSA. Four variables were therefore removed for the EFA (Poggendorff, Zöllner, antiTravel, and CrowdSize). The global MSA index after variable removal was 0.659.

Factors were extracted with a common factor analysis to reflect the variance shared between variables (i.e., the common variance). We used an oblique rotation (promax; see Costello & Osborne, 2005) because we had no reason to preclude factors to correlate.

A parallel analysis suggested a five-factor model, whereas only three factors were suggested by scree plot inspection (see Supplementary Figure S3). Because the eigenvalues for factors 4 and 5 were very close to those of a resampled dataset and below 1.0 (Kaiser, 1970; RF1: 3.058; RF2: 1.892; RF3: 1.055; RF4: 0.719; RF5: 0.497), we retained the three-factor model (TLI = 0.615; RMSEA = 0.112 with 90% CI [0.093, 0.134]). The three factors together explained 37.6% of the variance (RF1: 15.6%; RF2: 13.8%; RF3: 8.2%). Loadings are reported in Table 3. According to a simulation published in Hair, Black, Babin, Anderson, and Tatham, (2018), loadings

	RF1	RF2	RF3
CrowdPeri	0.144	–0.341	**0.603**
Contrast	0.010	–0.088	**0.586**
HC black	**0.826**	0.147	–0.135
HC white	**0.887**	0.160	–0.161
EX black	**0.842**	0.135	–0.028
EX white	**0.596**	0.082	0.163
NBack	–0.038	0.204	0.249
Orient	–0.109	0.205	0.228
RDK hor	–0.261	0.155	–0.017
RDK rad	–0.129	0.243	–0.028
ReacTime	0.041	**0.646**	–0.071
proTravel	0.085	0.288	0.113
proSac	0.077	**0.660**	–0.130
antiSac	–0.067	**0.799**	–0.096
VisAcuity	–0.068	–0.047	0.507
VBM	–0.018	0.208	**0.586**
VisSrch4	0.203	0.544	0.059
VisSrch16	0.297	0.515	–0.017

Table 3. Rotated factor loadings from an EFA on the visual variables only and after promax (i.e., oblique) rotation. A color scale from blue (negative loadings) to red (positive loadings) is shown. Factor loadings larger than 0.55 are highlighted (bold).

larger than 0.55 are considered as significant with a sample size of 100.

The first factor was mainly related to the Honeycomb and Extinction variables (HC black, HC white, EX black, EX white). Both illusions are related to visual perception in the periphery and were here (Table 2) and previously shown to strongly correlate (Bertamini et al., 2019). The second factor mainly loaded on variables related to reaction times, such as ReacTime, VisSrch4, and VisSrch16, and to the prosaccade and antisaccade paradigm (e.g., proSac, antiSac). The third factor strongly loaded on the contrast detection, visual backward masking (VBM; i.e., a measure of spatiotemporal perception, which may reveal specifically tuned to gaming), and crowding paradigm, which is a measure of visual acuity in the periphery. Interfactor correlations were mostly weak (RF1-RF2: $r = 0.009$; RF1-RF3: $r = -0.011$; RF2-RF3: 0.260). Hence, it seems that there is no strong and unique factor underlying visual perception in action video game players but rather multiple factors, which only explain a small proportion of the variability.

Regression

First, a multiple regression model was computed to estimate how much variance in the players' rank is accounted for by visual performance, gaming skills, and personality traits. Second, we examined the accuracy
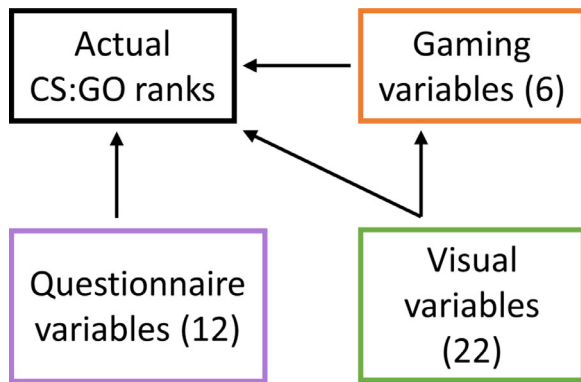
Figure 4. Schematic representation of the path model computed to determine to what extent the players' rank can be predicted by the visual, gaming, and questionnaire variables. The numbers in brackets indicate the number of variables considered. The visual variables not only regressed on the actual CS:GO ranks but also on the gaming variables.

in the prediction of the ranks while reducing the high-dimensionality of the model (i.e., the number of variables). To this aim, we computed an elastic net model, which extracted the variables with stronger predictive power. Importantly, note that the CS:GO related questionnaire variables (i.e., Best CS:GO rank, NbHoursPerWeek, and NbTotalHours) and amount of sleep (NbHoursSleep) were not included for further analysis. Indeed, performance in several domains, such as games, sports, and music, is known to be closely related to the amount of practice (e.g., Macnamara et al., 2014). Here, we aimed at examining whether players' rank can be predicted from variables that are not specifically related to the amount of training, namely visual perception, gaming skills, and personality traits.

Path model

We wondered to what extent the visual, gaming, and questionnaire scores predict the actual CS:GO ranks of the players, and how gaming variables relate to visual variables. Hence, we designed a complex, multiple regression model (i.e., a path model) schematically represented in Figure 4. The actual CS:GO rank is an outcome variable (i.e., endogenous variable), whereas the visual and questionnaire variables are predictors (i.e., exogenous variables). The gaming variables are both outcomes and predictors.

Standardized path coefficients are reported in Table 4 (no correction was applied for multiple comparisons). The visual, gaming, and questionnaire variables explained 69.6% of the variance of the CS:GO ranks. Between 12.9% and 37.4% of the variance of each gaming variable was accounted for by the visual variables. Some gaming variables showed significant standardized path coefficients on the CS:GO ranks,

and so did some variables related to visual paradigms (crowding, Honeycomb illusion, Zöllner illusion, random dot kinematograms). Similarly, visual variables showed some significant standardized path coefficients on the gaming variables. For example, the ReacTime variable significantly loaded on the Shoot, Track, and Hold gaming variables.

Hence, it seems that the variance in the players' rank is largely accounted for by performance in visual perception, specific gaming skills, and personality traits.

Elastic net model

Using the scikit-learn package in Python (Pedregosa, Varoquaux, Gramfort, Michel, Thirion, Grisel, … Duchesnay, 2011), we aimed at predicting the actual CS:GO players' ranks by fitting an elastic net model (Zou & Hastie, 2005), i.e., a regressor, which both uses L1 and L2 regularizations, therefore reducing the dimensionality of the model and the risk of overfitting.

The dataset was split into a training (80%) and test (20%) set. Using a search grid with a fivefold cross-validation, we optimized the model's generalization performance on the training set by tuning two hyperparameters, namely alpha and the L1 ratio (i.e., L1/(L1+L2)). The lower alpha, the more complex the model (i.e., less strict regularization).

Performance on the training set was optimized for alpha = 0.15 and with an L1 ratio of 0.45. With these values for the hyperparameters, the training and test set accuracies were $r^2 = 0.643$ and $r^2 = 0.210$, respectively. The MSEs for the training and test sets were 0.21 and 0.26, respectively. In contrast, a dummy regressor resulted in an MSE of 0.60 and 0.37 in the training and test sets, respectively. The following variables had nonzero coefficients: CrowdSize (0.034), CrowdPeri (-0.022), HC white (0.088), Zöllner (-0.106), proSac (0.080), VisAcuity (-0.033), VisSrch4 (0.011), Shoot (0.222), Spray (0.065), Track (0.166), Flick (0.005), BIS (0.052), HEXACO CO (-0.008), HEXACO OP (-0.089). Gaming variables were expected to show non-zero coefficients, because they are obviously related to the players' rank (Table 2).

Our results suggest that the Honeycomb illusion and crowding variables are predictors of the players' rank, i.e., players who perceived barbs in larger areas (HC white) and who needed a smaller optotype to achieve 75% of performance (CrowdSize) tend to have higher ranks. Note that both paradigms are related to visual perception in the periphery. However, participants with higher ranks tend to have worse visual acuity in the fovea (VisAcuity) and to be more susceptible to the Zöllner illusion (ZN). In addition, our results suggest that faster reaction times (proSac and VisSrch4) are associated with higher ranks. Lastly, participants with weaker conscientiousness (HEXACO CO), weaker openness to experience (HEXACO OP), and with

	Actual CS:GO rank	Shoot	Spray	Track	Hold	Flick	Peek
CrowdSize	0.230**	−0.049	0.005	−0.155	0.221*	−0.025	−0.017
CrowdPeri	0.139	0.176	−0.043	−0.139	−0.133	0.127	−0.166
Contrast	0.096	−0.089	−0.073	−0.115	0.004	−0.039	0.074
HC black	0.029	0.060	0.039	−0.057	0.048	0.080	−0.010
HC white	0.297*	0.084	0.163	0.108	−0.048	−0.277	0.005
EX black	−0.157	0.051	−0.043	−0.186	0.175	−0.070	0.050
EX white	−0.192	0.051	0.026	0.367**	0.013	0.390**	0.184
Poggendorff	−0.022	−0.243*	0.078	0.032	0.078	0.055	0.040
Zöllner	−0.303***	−0.118	−0.033	0.123	−0.182	0.130	−0.028
Nback	−0.055	−0.099	−0.032	−0.126	−0.012	−0.063	0.232
Orient	0.067	0.121	0.295**	0.149	0.060	0.050	0.039
RDK hor	−0.212*	0.178	0.268*	0.370***	0.206	0.188	0.021
RDK rad	0.135	0.059	−0.011	−0.256*	−0.090	0.095	0.153
ReacTime	−0.030	0.272*	0.011	0.226*	0.238*	−0.023	−0.048
proTravel	0.124	−0.055	−0.253	−0.162	0.231	−0.052	0.055
proSac	0.167	0.190	0.175	−0.046	−0.050	−0.075	0.065
antiTravel	−0.065	0.088	0.417*	0.255	−0.196	0.118	0.041
antiSac	0.010	−0.140	−0.116	−0.048	−0.054	0.150	−0.088
VisAcuity	−0.081	0.040	−0.139	0.100	−0.037	−0.412***	−0.070
VBM	−0.047	−0.019	0.148	0.078	0.165	0.147	0.036
VisSrch4	−0.015	0.057	−0.088	0.269	0.180	0.127	−0.092
VisSrch16	0.116	−0.119	−0.159	−0.304	−0.271	−0.254	−0.061
Shoot	0.223**						
Spray	0.122						
Track	0.473***						
Hold	−0.095						
Flick	0.072						
Peek	0.029						
AQ	0.088						
BIS	−0.130						
CI	0.128						
HEXACO HH	0.100						
HEXACO EM	−0.117						
HEXACO EX	0.195*						
HEXACO AG	0.009						
HEXACO CO	−0.213*						
HEXACO OP	−0.254**						
Handedness	0.020						
O-LIFE	0.097						
PRFd	−0.160						
r^2	0.696	0.244	0.220	0.374	0.250	0.296	0.129

Table 4. Standardized path coefficients (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$) from the path model (see Figure 4) and variance explained (r^2) of each endogenous variable. The strength of the standardized path coefficients is indicated with a color scale from blue (negative loadings) to red (positive loadings).

higher score on the Barratt Impulsiveness Scale (BIS), tend to have higher ranks.

Overall, the model drastically reduced the dimensionality of the dataset (from 40 to 14 variables) by extracting the variables with stronger predictive power, such as the Honeycomb illusion and crowding variables.

Discussion

Summary

We tested 94 CS:GO players ranging from beginners to experts with 12 visual paradigms, specific gaming skills, and personality traits to examine what aspects are associated with expertise, and whether there is a unique, common factor underlying visual perception in AVGPs.

First, we observed only weak correlations between visual variables, except between variables that belong to the same paradigm, which can be taken as a measure of reliability. In addition, gaming variables showed strong intercorrelations. A factor analysis revealed three factors explaining about 38% of the variance, which suggests a poor factor structure.

Second, a path model showed that almost 70% of the variance of the actual players' rank is predicted by visual, gaming, and questionnaire scores. Not only gaming variables but also some visual and questionnaire scores showed strong loadings on the players' rank.

Last, we computed an elastic net model to select the features with stronger predictive power on the actual ranks (i.e., to reduce the dimensionality of the dataset). The model retained 14 variables (among which seven were visual variables), which altogether led to better predictions of the ranks compared to a dummy model. The visual variables, which were retained in the elastic net model and showed significant standardized loadings in the path model, were CrowdSize (crowding size), HC white (Honeycomb illusion with white barbs), and the Zöllner illusion. Note that the best CS:GO rank, amount of training (NbHourPerWeek and NbTotalHours), and amount of sleep (NbHoursSleep) were not included in the path and elastic net models.

Importantly, the path model accounted for a larger proportion of the variance in the data compared to the elastic net model ($r^2 = 0.696$ versus $r^2_{training} = 0.643$, respectively), because the former used more variables than the latter (40 versus 14 variables, respectively). While the dimensionality of the dataset was reduced in the elastic net model, the decrease in performance compared to the path model was rather small, which suggests that most variables do not significantly predict the players' rank. However, the test set accuracy was much lower than the training set accuracy in the elastic net model ($r^2_{test} = 0.210$ versus $r^2_{training} = 0.643$), which

suggests overfitting even though the elastic net model showed a better test *MSE* compared to a dummy regressor. The small test sample size (20%, i.e., 19 participants only) may partially explain the rather low test set accuracy.

We expected many aspects of gaming to rely on (low-level) visual skills. However, our results suggest that there is no strong common factor for visual perception in CS:GO players. Similarly, there is only weak evidence for a common factor for visual perception in general (Mollon et al., 2017; Tulver, 2019). For example, many specific factors were reported in oculomotor tasks (Bargary et al., 2017), in the perception of faces (Verhallen et al., 2017), and in the susceptibility to visual illusions (e.g., Cretenoud et al., 2019; Grzeczkowski et al., 2017). More generally, basic visual paradigms only weakly correlate with each other (e.g., Cappe et al., 2014).

Positive association between peripheral vision and the players' rank

Rather than a strong common factor for visual perception in CS:GO players, specific visual paradigms and personality traits seem to be strongly predictive of the players' rank. For example, players who perceived more barbs in the Honeycomb white illusion, tended to have higher ranks. Since the four variables extracted from the Honeycomb and Extinction paradigm (HC black, HC white, EX black, and EX white) strongly correlate with each other (Table 2), we expected that either all four variables or none would be significantly associated with the players' rank. However, only one variable (i.e., HC white) showed a non-zero coefficient in the elastic net model (0.088) and a significant standardized path loading (0.297), suggesting that not all variants of the illusions are associated with the players' rank.

Interestingly, similar illusion magnitudes were observed in the Honeycomb illusion with black and white barbs (HC black and HC white; see Supplementary Figure S2), while the mean extent of visible region was previously shown to be larger in the white compared to the black variant (Bertamini et al., 2019). A difference in the experimental design may explain the discrepancies in the results. To estimate the mean extent of the region in which barbs were visible, participants adjusted the size of an ellipse (i.e., on both x and y axes) in the present investigation, whereas a disk (i.e., a single dimension) was adjusted in Bertamini et al. (2019). The background images were the same in both studies. Note that barbs (or disks in the Extinction illusion) were removed during the adjustment in Bertamini et al. (2019), unlike in the present investigation. Despite these differences,

an interaction between the illusion type (Extinction, Honeycomb) and contrast polarity (black, white) was observed in both studies. It may be worth considering that the magnitude of these illusions conflate a perceptual and a response bias aspect. Participants may differ in the tendency to report what they may "know" rather than what they see, or, even without awareness of this, to "cheat" by not maintaining fixation.

The crowding paradigm similarly seems to be a strong predictor of the players' rank. Higher ranks were associated with a better visual acuity in the periphery, as reflected by the CrowdSize variable (standardized path coefficient: 0.230; coefficient from the elastic net model: 0.034). Although Green and Bavelier (2007) previously reported an increased spatial resolution in AVGPs compared to NVGPs, we observed a negative association between spatial resolution, as measured with a crowding paradigm (CrowdPeri), and the players' rank (coefficient from the elastic net model: −0.022). However, further investigation is needed to verify this association, since CrowdPeri did not show up as a significant coefficient in the path model, which may indicate that the association is unreliable. In addition, a radial-tangential anisotropy was reported in crowding (Chung, 2013; Greenwood, Szinte, Sayim, & Cavanagh, 2017), suggesting that the association may be different along the horizontal axis.

Both the Honeycomb illusion and crowding paradigm are related to peripheral vision and were strongly associated with the players' rank. However, the Honeycomb and crowding variables did not correlate ($M = 0.012$, $SD = 0.067$; Table 2). As in foveal vision, it is likely that vision in the periphery is multifactorial, i.e., there is no strong common factor for peripheral vision. For example, Yashar, Wu, Chen, and Carrasco (2019) reported no common mechanism for crowding across different visual features. The authors tested different visual features under crowding to determine at which processing stage crowding occurs. They observed that orientation and spatial frequency errors were interdependent, whereas orientation and color errors were independent, suggesting that peripheral vision is feature-dependent.

While different features are likely processed differently in the periphery, our results suggest that peripheral vision in general plays an important role in CS:GO. Specifically, it seems that high-rank players have better peripheral vision compared to low-rank players, which adds to previous results reporting evidence for better peripheral vision in AVGPs compared to NVGPs (for a review and meta-analysis, see Chopin et al., 2019). Similarly, increased peripheral visual skills are beneficial to team sports players, such as basketball or soccer players (Faubert & Sidebottom, 2012; Knudson & Kluka, 1997). However, note that the crowding variables only weakly correlated with the players' rank (CrowdSize: $r = 0.085$, $p = 0.414$; CrowdPeri: $r =$

0.057, $p = 0.656$; Table 2), suggesting that their role in CS:GO is important when interacting with other specific skills only. In contrast, the correlation between the Honeycomb white variable and players' rank was medium to large ($r = 0.298$, $p = 0.003$), according to Cohen (1988) and Gignac and Szodorai (2016), respectively.

Negative association between central vision and the players' rank

Surprisingly, visual acuity in the fovea (VisAcuity) was negatively associated with the players' rank (coefficient from the elastic net model: −0.033). Patino, McKean-Cowdin, Azen, Allison, Choudhury, and Varma (2010) reported that central and peripheral visual acuities were negatively correlated in a large sample of subjects. Here, however, we observed a weak positive correlation between central (VisAcuity) and peripheral (CrowdSize) visual acuities ($r = 0.159$, $p = 0.129$; Table 2). It is therefore not completely unlikely that central and peripheral vision engage independently while playing video games, as was shown for reaching (Prado, Clavagnier, Otzenberger, Scheiber, Kennedy, & Perenin, 2005).

Other associations between visual paradigms and the players' rank

Players with higher ranks were associated with stronger susceptibility to the Zöllner illusion (standardized path coefficient: −0.303; coefficient from the elastic net model: −0.106). Further investigation may closely examine this association.

In addition, we observed other associations. However, these explained only a small proportion of the variance of the ranks and were not always consistent across analyses (path model vs. elastic net model), suggesting that they may be unreliable. For example, faster reaction times when making saccades or searching for a target were associated with higher ranks (coefficients from the elastic net model: proSac: 0.080, VisSrch4: 0.011). Similarly, Bosten and colleagues (2017) reported that the time spent playing computer games significantly correlated with a factor for oculomotor speed.

Previous studies suggested that action video games are associated with better performance in certain perceptual tasks. Some of these associations could however not be replicated here. For example, VGPs were reported to perform significantly better than NVGPs at discriminating contracting, but not expanding, elements in a radial random dot kinematograms paradigm (Hutchinson & Stocks, 2013). The authors suggested

that VGPs are more sensitive than NVGPs to visual characteristics, which are enhanced in gaming (e.g., contracting patterns) relative to those encountered in the real world (e.g., expanding patterns). Here, we did not observe any significant association between the players' rank and the performance in a radial random dot kinematograms (RDK rad). Note, however, that both contracting and expanding conditions were considered together in the RDK rad variable. In contrast, we observed that the performance in the horizontal random dot kinematograms (RDK hor) significantly loaded on the players' rank (standardized path coefficient: −0.212), even though the correlation between the two was only weak and nonsignificant ($r = 0.040$ $p = 0.706$; Table 2).

Li and colleagues (2009) reported that contrast sensitivity at intermediate and higher spatial frequencies was enhanced after action video game training, which suggests that high-rank players may have better sensitivity to contrast than low-rank players. However, we did not observe any significant association between contrast sensitivity and the players' rank. It seems unlikely that the spatial frequency used here (4.0 cy/arcdeg) was too low to find an effect, since a small but significant effect was previously reported with a spatial frequency of 3.0 cycles per degree. Likewise, while Li and colleagues (2010) previously reported that playing action game reduces the effects of backward masking, no such association was observed in the present investigation.

Similarly, we did not observe any significant association between the players' rank and perceptual speed (ReacTime), contrary to Dye and colleagues (2009). Importantly, we tested only gamers ranging from beginners to experts but not non-gamers, contrary to most previous studies, which may explain the discrepancies in the results. For example, it may be that training video game improves contrast detection and perceptual speed in NVGs but does not further improve with additional training.

Gaming variables

Among the six gaming variables that were extracted, four were retained in the elastic net model (Shoot, Spray, Track, and Flick) and two showed significant standardized path coefficients (Shoot and Track). To estimate to which extent the players' rank can be predicted from the performance in the six gaming variables, we computed another multiple regression model, in which only the gaming variables loaded on the actual CS:GO ranks. The six gaming variables accounted for 48% of the variance of the actual CS:GO ranks. Note that extracting more gaming variables could have resulted in a larger proportion of the variance explained. However, our results highlight that

the Shoot and Track variables (which showed up in both path and elastic net models) are building blocks for the game.

Questionnaire variables

De Hesselle, Rozgonjuk, Sindermann, Pontes, and Montag (2021) reported that lower conscientiousness, extraversion, and agreeableness were significantly associated with more time spent gaming. Here, the associations between personality traits and gaming variables or the players' rank were in general weak. However, two personality traits showed significant associations with the players' rank in the path and elastic net models, namely the HEXACO CO and HEXACO OP. Results suggest that players with low scores in conscientiousness (HEXACO CO) and openness to experience (HEXACO OP) tend to have higher ranks.

Limitations

While we only tested CS:GO players, our results may hold true for other action video games. Importantly, the present investigation does not allow us to claim that high-rank CS:GO players develop specific visual skills while playing, such as better visual acuity in the periphery. Neither can we infer from the data that specific visual skills or personality traits are required to become an excellent player. However, a reliable dose-response effect in intervention studies was suggested as evidence for a causal effect of action video gaming on perception (Chopin et al., 2019). Although we are not able to infer causality, our experimental design avoids the methodological shortcomings inherent to intervention studies (Boot et al., 2011), such as differential placebo effects driven by the treatment versus control interventions (e.g., Tetris-trained participants may predict that they will have a better post-training performance in a mental rotation task). Likewise, all participants were active gamers, reducing the risks of strategy changes impacting our results. We cannot exclude gender-specific effects since only male participants took part in the present study (e.g., gender disparity in mental rotation ability decreased following video game training; see Feng et al., 2007).

Not all paradigms that we classified as visual are purely visual. Indeed, some paradigms also tap into more cognitive aspects, such as inhibition and attention. Hence, it may be that the significant associations with the players' rank are related to a complex interaction between visual perception and cognition.

Importantly, power may be an issue given the large number of variables extracted and the moderate sample size. Hence, results must be considered with caution and replicated. False-positive results (i.e., spurious

associations) cannot be excluded given the large number of tests we computed. We do not have enough power to make conclusions on specific between-variable correlations in this study (Table 2). Instead, we aimed at showing that visual variables only poorly relate to each other in general. It is the pattern as a whole, which is important, not single, specific correlations.

Also, we do not have a measure of reliability for all variables, as not all variables were tested twice. Between-variable correlations may for example be underestimated because of poor or moderate reliability (Ackerman & Hambrick, 2020). However, note that reliabilities (as measured with intraclass correlations) were large for the central visual acuity (VisAcuity) and visual backward masking (VBM) variables, which suggests that variables measured with a staircase procedure show good reliability. Last, we considered the rank as a continuous variable, even though it is ordinal. As the distance between two ranks may not be constant, we consider this as a limitation of the present investigation.

Conclusions

To summarize, our results suggest that there is no strong common factor for visual perception in CS:GO players. However, the performance in some visual paradigms strongly predicts the players' rank. In particular, high-rank players seem to have better visual perception in the periphery, as measured with a crowding paradigm and the Honeycomb illusion, compared to lower-rank players. Even though causative relationships cannot be derived from these results, the present investigation gives clues about visual paradigms, which may be part of future training programs for esports.

Keywords: action video games, vision, common factor, prediction, visual acuity, honeycomb illusion

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