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Differences in eye movement characteristics between expert and non-expert eSports players: a systematic review and meta-analysis

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eSports is an emerging digital sport that has attracted widespread attention. As an activity that heavily relies on visual information, investigating the differences in eye movement characteristics between eSports players of varying skill levels is crucial for understanding the mechanisms underlying improvements in gaming performance. Therefore, the aim of this study was to systematically and comprehensively evaluate the differences in the characteristics of eye movements between expert and non-expert eSports players by integrating existing studies through a systematic review and meta-analysis approach. A systematic search was conducted across the PubMed, Scopus, and Web of Science databases, with the search cutoff date set to July 20, 2024. A total of seven studies, involving 165 participants, were ultimately included in the analysis. The aggregated results show that expert eSports players have a significantly shorter average fixation duration compared to non-expert players, with a moderate amount of effect size (SMD = -0.66; 95% CI: -1.01, -0.30; $P<0.05$). There is no significant difference in the average number of fixations between expert and non-expert eSports players (SMD = -0.22; 95% CI: -0.55, -0.99; $P=0.58$). Regarding eye tracking characteristics within areas of interest, expert players exhibit more targeted visual strategies and devote greater visual attention to key elements of the game. These findings provide a scientific basis for eSports training and contribute to developing more effective training methods and strategies, thereby improving players' competitive performance. Future research could further investigate the relationship between eye movement characteristics and eSports performance and develop personalized training programs based on eye movement data.

Keywords eSports, Eye movement, Expertise, Systematic review, Meta-analysis

eSports is a new form of competitive sport that takes place in virtual environments[1]. eSports, which combines entertainment and competition, has attracted increasing attention[2,3]. With the rapid growth of eSports, there has been a steady upward trend in scientific publications in this area[4]. The academic community has conducted extensive research on the various characteristics of eSports players and the mechanisms of their performance in games, trying to identify the key factors that influence the performance of eSports players. However, our current understanding of the various factors that influence gaming performance is still relatively limited[5]. In recent years, research on eye movement characteristics has provided new insights into the mechanisms underlying eSports players' gaming performance. As a competitive activity requiring high cognitive engagement, eSports players must possess exceptional visual search abilities[6]. Existing studies have demonstrated that visual search efficiency not only affects the speed of extracting critical in-game information but is also linked to decision-making accuracy and reaction time[7]. Consequently, effective eye movement behaviors play a decisive role in gaming performance, particularly in fast-paced, information-dense eSports scenarios. Given this, investigating

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eye movement characteristics holds significant practical value for further exploring the factors influencing eSports players' performance.

Comparing the differences between experts and non-experts to identify the underlying mechanisms of high performance is a widely used approach[8]. In traditional sports, this research paradigm has proven to be an effective method for uncovering the factors that contribute to skill development and providing a crucial foundation for enhancing athlete performance[9–12]. As research in the field of eSports increased, similar research paradigms have been applied to this area. The criteria for distinguishing between expert and non-expert eSports players primarily include the following aspects: membership in professional teams, duration and frequency of gameplay, and official rank. In the early stages of research, investigators focused primarily on comparing the differences in brain characteristics and neural abilities among gamers of different skill levels[13]. As research progresses, investigators have shifted their focus to examining differences in visual behavior among gamers—a transition closely tied to eSports' heavy reliance on visual search abilities. For instance, in League of Legends, gamers must monitor various dynamic elements on the screen, such as opponent positions, teammate statuses, and map changes, to make quick decisions and take appropriate actions[14]. The literature suggests that frequent eSports players perform better on visual search tasks than novices. For example, Hubert-Wallander et al. (2011) provided insight into this claim by using two types of visual search tasks—measuring reaction time and accuracy. Their results showed that the performance of the gamer group on visual search tasks was superior to that of the non-gamer control group[15]. The study by Li et al. (2022) supports this view. Their results suggest that video game players have shorter response times and fixation durations on visual search tasks compared to non-video game players[16].

To gain a deeper understanding of visual search behavior in eSports, researchers have increasingly adopted eye tracking technology. Eye tracking technology plays a crucial role in revealing the eye movement characteristics of eSports players. This technology can precisely record eye movement trajectories during gameplay, including the location of fixations, fixation duration, number of fixations, and the path of eye movements[17]. In fact, many researchers have used eye tracking techniques to measure the gaze behavior of traditional sports athletes to discover their patterns of visual attention allocation during training[18]. With the development of eSports, eye tracking technology has begun to be integrated into this field. To date, the application of eye tracking technology in eSports research has yielded initial results, providing new perspectives for understanding how players process visual information in highly complex gaming environments.

Although existing literature has attempted to explore the eye movement characteristics of players at different skill levels, there is still considerable divergence in the findings regarding the eye movement characteristics of expert and non-expert eSports players. For example, Jeong et al. (2024) reported significant differences in eye movement metrics such as average fixation duration between expert and non-expert eSports players[14], while other studies failed to find clear differences[19]. This makes it difficult to draw comprehensive conclusions regarding eye-movement characteristic differences between expert and non-expert eSports players. This divergence may stem from multiple factors: First, most studies suffer from inadequate sample sizes and insufficient statistical power. Second, there are variations in game genres across different studies (e.g., MOBA games vs. FPS games). Third, differences exist in stimulus presentation methods (Realistic stimulating environment versus Simulated stimulating environment)[20]. To address this issue, conducting a systematic review and meta-analysis is crucial. By synthesizing data from multiple studies, systematic reviews and meta-analysis can reduce the limitations of individual studies and provide more reliable conclusions, allowing for a more accurate identification of the differences in eye movement characteristics between expert and non-expert eSports players[21]. Moreover, no systematic reviews or meta-analysis have yet been conducted on the eye movement characteristics of eSports players. Ultimately, the results from such research not only contribute to deeper academic discussions but also offer practical insights for eSports training.

This study aims to employ systematic review and meta-analysis methods to integrate existing research findings and analyze the potential differences in eye movement characteristics between expert and non-expert eSports players. Specifically, we examine the following oculomotor measures: fixation duration, number of fixation, and area of interest (AOI) analysis.

Methods

This systematic review followed the principles outlined by the PRISMA guidelines[22]. This protocol was registered on the PROSPERO (CRD42024571216).

Search strategy

For a thorough and systematic review of relevant studies, we comprehensively searched three major electronic databases (PubMed, Web of Science, and Scopus) up to July 20, 2024. Specific term combinations were connected using Boolean operators (AND/OR) within each database to ensure both precision and comprehensiveness in the search results. We found that when using 'eye movement' and 'esports' as search terms alone, the number of eligible studies was limited. Therefore, we used a more relaxed search algorithm. The relevant retrieval strategy was as follows: (vision OR visual* OR eye* OR gaze OR gazing OR ocular OR oculomotor OR pupil diameter OR eye movement OR quiet eye OR saccad* OR fixation track OR smooth pursuit) AND (novice* OR expert* OR skill* OR experience OR level* OR professional*) AND (player* OR gamers OR athlete* OR game player*) AND (eSports OR video game* OR e-sports). To further ensure comprehensive coverage, additional manual searches were conducted using Google Scholar.

Selection criteria

The inclusion criteria for the final set of studies were selected based on the PECOS (Participants, Exposure, Comparator, Outcome, Study Design) framework[23].

Participants: The studies included in the analysis must involve eSports players, both expert and non-expert, without restrictions on gender or age.

Exposure: The research should utilize eye tracking technology to assess the eye movement characteristics of eSports players, either in a simulated stimulating environment (e.g., videos/images) or a Realistic stimulating environment (e.g., live events).

Comparator: The studies must include at least one comparison between expert and non-expert eSports players.

Outcome: The relevant outcomes should relate to eye movement characteristics, including number of fixation, fixation duration, first fixation duration, area of interest (AOI), saccade duration, saccade velocity, and saccade length.

Study Design: Any study design.

A study is disqualified if it satisfies any of the following requirements: (1) Research that examined eye movement characteristics using generic paradigms, such as visual search tasks; (2) Meta-analyses or review articles; (3) Papers that were not peer-reviewed or classified as grey literature; (4) Non-English language publications.

Literature screening and data extraction

During the literature screening process, we used the reference management software EndNote 20.0 to automatically remove duplicates. Two independent researchers (CYH and CJH) then screened the literature and extracted data based on the inclusion and exclusion criteria. For studies that met the inclusion criteria, we extracted data such as the first author and year of publication, demographic characteristics of participants, stimulus method, and means and standard deviations (or t-values or F-values) of the outcome measures. If the required data were not included in tables or supplementary materials but were presented in graphical form, we used the Graph Digitizer software (Digitizelt, Germany) to extract the relevant data from the figures[24]. The extracted data will then be cross-verified by two independent researchers to ensure accuracy. Notably, for studies involving more than two experimental groups (e.g., expert, intermediate, and non-expert groups), we primarily extracted and analyzed data from the highest and lowest-level groups. In cases where a disagreement arose between the two researchers, a third researcher (YCL) was brought in to resolve the issue.

Risk of bias assessment of studies

Given that studies comparing expert and non-expert eSports players are inherently non-randomized, this study used the Cochrane Risk of Bias Assessment Tool for Non-randomized Studies (RoBANS) to assess the risk of bias[25]. This assessment tool demonstrated moderate reliability and good validity. There are six categories in all, and each one is categorized as having a "high risk," "unclear risk," or "low risk" of bias. Two researchers (CYH and CJH) independently assessed the included studies. In cases where disagreement arose during the evaluation process, a third researcher (YCL) was brought in to discuss the issue until a consensus was reached.

Data synthesis

Meta-analysis was performed using Review Manager 5.4. We calculated the means and standard deviations of the dependent variables and used the standardized mean difference (SMD) to represent the effect sizes. According to Cohen's guidelines for evaluating effect sizes, an effect size of less than 0.2 is considered small, an effect size between 0.2 and 0.8 is considered moderate, and an effect size greater than 0.8 is considered large[26]. For each outcome, we calculated the weighted average effect size and the 95% confidence intervals (95% CI) to determine whether the effect sizes were significantly different from zero. In addition, we assessed between-study heterogeneity using I^2 statistics. High heterogeneity was defined as $I^2 > 75\%$, moderate heterogeneity as 25–75%, and low heterogeneity as <25%. A fixed effects model was employed when $I^2 < 50\%$ with $p \geq 0.1$, while a random effects model was adopted when $I^2 \geq 50\%$ with $p < 0.1$. To investigate potential sources of heterogeneity, subgroup analyses were conducted based on key factors including study region and type of stimulus. Sensitivity analyses were performed to evaluate the robustness of the results. According to Chap. 5 of the Cochrane Handbook, a funnel plot asymmetry test should be conducted only if the number of studies included is at least 10[27]. To accurately assess publication bias, Egger's test was performed on the data set using Stata 17.0. Statistical significance was considered if the p value was less than 0.05.

Results

Screening results

Figure 1 shows a detailed flowchart of the literature search, screening, and selection process for this systematic review and meta-analysis. A comprehensive search of three databases yielded a total of 3,655 records. After automatic removal of duplicates and screening based on titles and abstracts, 40 studies were identified as potentially eligible and underwent full-text review. Ultimately, seven studies were selected for systematic review and meta-analysis based on inclusion and exclusion criteria[14,19,28–32].

Table 1 provides a detailed summary of the characteristics of the seven studies included in this review. A total of 165 participants took part in all included studies, comprising 84 expert eSports players and 81 non-expert eSports players. These studies were published between 2016 and 2024. Studies were from Japan ($n = 2$)[14,30], the United States ($n = 1$)[28], China ($n = 1$)[31], Ireland ($n = 1$)[32], Germany ($n = 1$)[19], and Brazil ($n = 1$)[29]. Stimulus types included realistic stimulating environment and Simulated stimulating environment (FIFA 21 Screenshots) with examples of games or applications such as Dota 2, Gran Turismo, FIFA 19, StarCraft, League of Legends, FIFA 21, and Assetto Corsa Competizione. Outcome measures covered multiple dimensions of fixation behavior, including fixation duration AOI, Number of fixations on AOI, averaged number of fixations, averaged fixation duration, saccade velocity, saccade number, saccade length, and fixation percentage on AOI.

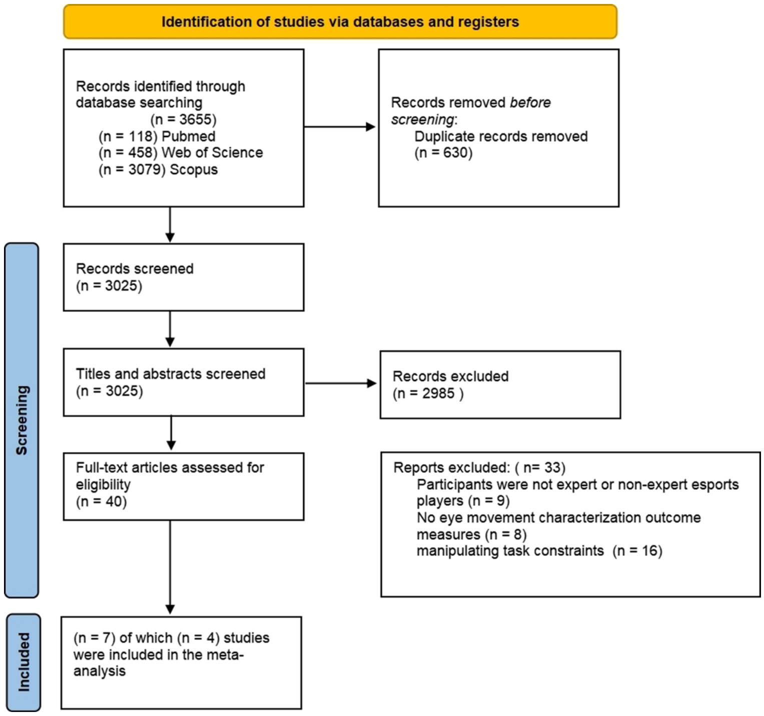

Fig. 1. Flow chart of literature screening and inclusion.

Authors/Year	Region	Participants	Stimulus	Outcome measures
Castaneda et al., 2016[28]	USA	E: $n=9$ C: $n=7$	Realistic stimulating environment (Dota2)	Fixation duration on AOI
Gotardi et al., 2019[29]	Brazil	E: $n=10$ C: $n=10$	Realistic stimulating environment (racing video game Gran Turismo)	Fixation duration on AOI Number of fixations on AOI
Bickmann et al., 2020[19]	Germany	E: $n=11$ C: $n=10$	Realistic stimulating environment (FIFA 19)	Averaged number of fixations Averaged fixation duration Fixation duration on AOI Number of fixations on AOI
Jeong et al., 2022[30]	Japan	E: $n=7$ C: $n=9$	Realistic stimulating environment (StarCraft)	Fixation duration on AOI Saccade velocity Saccade number Saccade length
Jeong et al., 2024[14]	Japan	E: $n=11$ C: $n=9$	Realistic stimulating environment (League of Legends)	Averaged number of fixations Averaged fixation duration Percentage of fixation on AOI
Wang et al., 2024[31]	China	E: $n=14$ C: $n=14$	Simulated stimulating environment (FIFA 21 Screenshots)	First fixation duration Averaged number of fixations Averaged fixation duration Number of fixations on AOI
Joyce et al., 2024[31]	Ireland	E: $n=22$ C: $n=22$	Realistic stimulating environment (Assetto Corsa Competizione)	Averaged number of fixations Averaged fixation duration

Table 1. Characteristics of included literature ($n=7$). AOI = area of interest; E = Expert; C = Non-expert.

Quality assessment

Two researchers independently assessed the seven included studies. The results revealed some common problems when assessing blinded outcomes. Notably, none of the studies mentioned blinding of outcome assessors, indicating a potential risk of unclear bias in the assessment process. Furthermore, two studies only reported data for some of the areas of interest (AOI) and not for all relevant AOIs[28]. This selective reporting could increase the risk of high bias. Detailed evaluation information can be found in Table 2.

Averaged fixation duration over the whole trial

Of the seven included studies, four provided data on average fixation duration, including four expert groups ($n=69$) and four non-expert groups ($n=64$)[14,19,31,32]. After testing for heterogeneity, it was found the degree of heterogeneity between studies was low (I^2 = 24%; $p>0.1$), and therefore a meta-analysis was performed using a fixed effects model. The results showed that expert eSports players had significantly shorter average fixation

Study	Domain 1	Domain 2	Domain 3	Domain 4	Domain 5	Domain 6
Castaneda et al., 2016	Low risk	Low risk	Low risk	Unclear risk	Low risk	High risk
Gotardi et al., 2019	Low risk	Low risk	Low risk	Unclear risk	Low risk	Low risk
Bickmann et al., 2020	Low risk	Low risk	Low risk	Unclear risk	Low risk	Low risk
Jeong et al., 2022	Low risk	Low risk	Low risk	Unclear risk	Low risk	Low risk
Jeong et al., 2024	Low risk	Low risk	Low risk	Unclear risk	Low risk	Low risk
Wang et al., 2024	Low risk	Low risk	Low risk	Unclear risk	Low risk	Low risk
Joyce et al., 2024	Low risk	Low risk	Low risk	Unclear risk	Low risk	High risk

Table 2. ROBANS risk of Bias assessment for included studies. Domain 1: the selection of participants. Domain 2: confounding variables. Domain 3: the measurement of exposure. Domain 4: the blinding of outcome assessments. Domain 5: incomplete outcome data. Domain 6: selective outcome reporting.

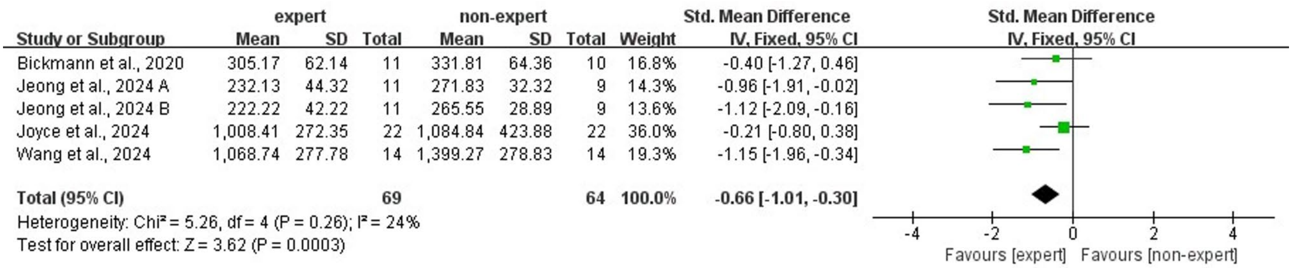

Fig. 2. Forest plot of averaged fixation duration over the whole trial.

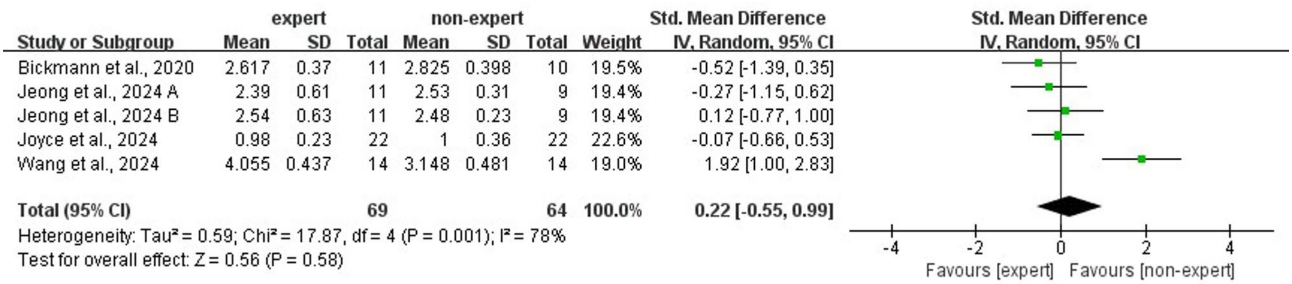

Fig. 3. Forest plot of Averaged number of fixations over the whole trial.

duration compared to non-expert players ($p < 0.05$). The effect size between the two groups was moderate (SMD = -0.66; 95% CI: -1.01, -0.30; $p < 0.05$) (Fig. 2). An Egger's test was performed, which gave a result of $p = 0.123$, which is not statistically significant. Therefore, there is no evidence of publication bias.

Averaged number of fixations over the whole trial

Of the seven studies analyzed, four specifically examined the average number of fixations between expert and non-expert eSports players. These studies included data from four expert groups ($n = 69$) and four non-expert groups ($n = 64$)[14,19,31,32]. The heterogeneity test revealed significant variability between studies ($I^2 = 78\%$; $p < 0.05$), indicating that a random effects model should be used for meta-analysis. The results showed no significant difference in the average number of fixations between the two groups, with a moderate effect size (SMD = -0.22; 95% CI: -0.55, -0.99; $p = 0.58$; see Fig. 3). An Egger's test was performed, which gave a result of $p = 0.632$, which is not statistically significant. Therefore, there is no evidence of publication bias.

To examine potential confounders and sources of heterogeneity across studies, we conducted a subgroup analysis based on study region and stimulus type. First, the subgroup analysis based on the study region revealed differences between Asia and Europe (Fig. 4). In Asia, the effect size was SMD = 0.58 (95% CI: -0.72, 1.89; I^2 = 84%), while in Europe it was SMD = -0.21 (95% CI: -0.70, 0.28; I^2 = 0%). The p value between groups was 0.27 ($p > 0.05$), indicating that there is no statistically significant difference between Asia and Europe.

Subgroup analysis based on stimulus type (Fig. 5) showed that the effect size for the Realistic stimulating environment was SMD = -0.16 (95% CI: -0.54, 0.23; I^2 = 0%), while for the simulated stimulating environment it was SMD = -0.16, SMD = 1.92 (95% CI: 1.00, 2.83; I^2 = not applicable). A statistically significant difference was

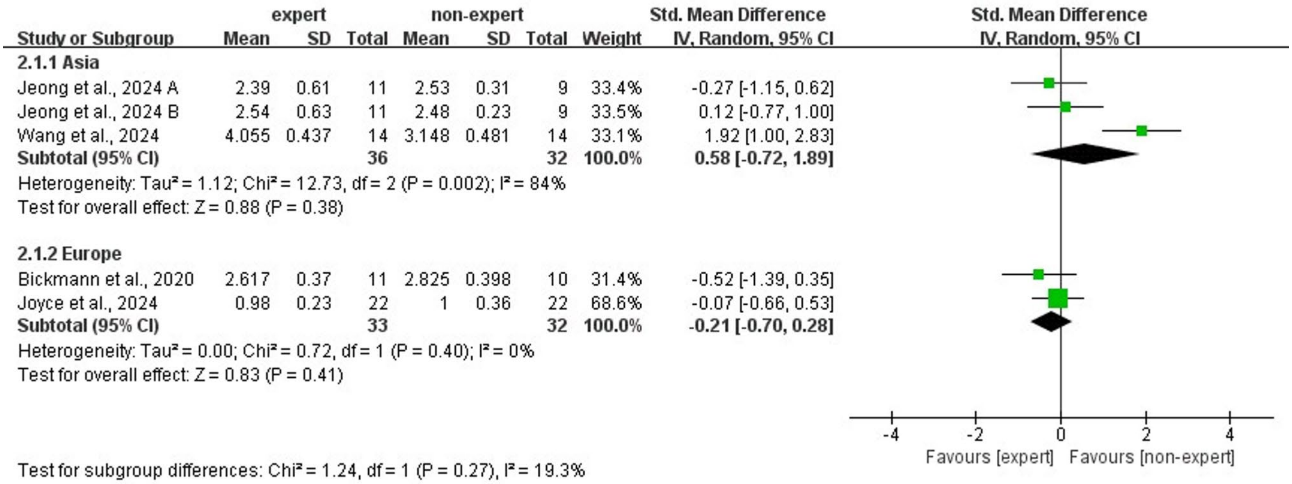

Fig. 4. Subgroup analysis based on study region.

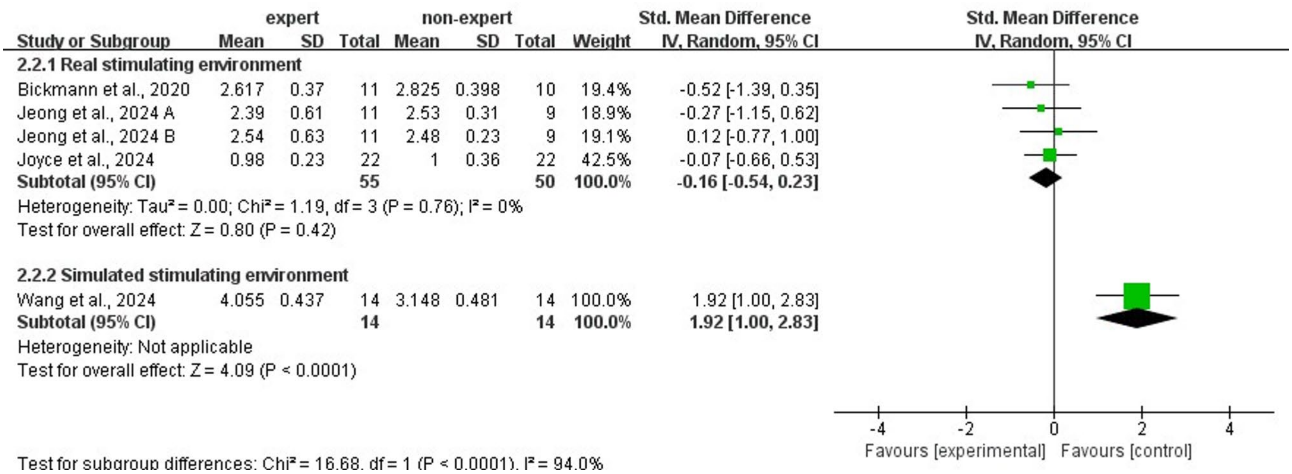

Fig. 5. Subgroup analysis based on stimulus type.

observed between the two groups ($p < 0.0001$). It is worth noting that after the exclusion of Wang et al. (2024), the I^2 value dropped markedly from 78 to 0%, indicating that this study may be the primary source of heterogeneity.

Eye movement characteristics on the area of interest

Seven studies were included, all of which provided eye tracking data for AOI[14,19,28–32] (see Table 3). However, due to the differences in the game types used and the variability in AOI definitions and numbers, a meta-analysis of the AOI eye tracking data was not possible. Therefore, a descriptive analysis was conducted to examine the eye tracking characteristics of expert and non-expert eSports players within these AOI.

The results showed that the researchers created approximately eight AOIs on average (M = 7.86, SD = 5.19, min = 4, max = 20). Notably, three studies did not specify how the AOIs were defined[29,30,32]. Four studies reported results on average fixation duration in AOIs[19,28–30]three of which reported differential significance in some AOIs compared to non-expert eSports players[19,30]. Three studies reported the number of fixations within AOIs[19,29,31]. Two of these studies found that expert players had significantly more fixations in certain AOIs compared to non-expert players ($p < 0.05$)[19,29], while the third study did not report any significant differences[31]. In addition, two studies reported the fixation rate for each AOI as a percentage[14,32]. Regarding fixation transitions (i.e., changing gaze from one AOI to another), one study found a significant difference between expert and non-expert ($p < 0.001$) and found that expert compared to non-expert made fewer repeated checks within the same AOI required ($p < 0.001$).

We identified several differences in visual strategy allocation between expert and non-expert eSports players. Specifically, expert eSports players use more targeted visual strategies. For example, in games like FIFA and StarCraft, expert eSports players tend to focus more of their visual attention on critical elements such as the minimap and tactically important areas. Moreover, expert eSports players demonstrated a higher frequency of gaze transitions and a lower need for repeated fixations within the same AOI ($p < 0.001$). However, not

Authors/Year	Area of Interest	AOI definition method	Conclusions
Castaneda et al., 2016[28]	The study identified twenty AOIs, detailing three areas: (1) the minimap, (2) HP/Mana, (3) the shop button	Defined by experts in the field of eSports	Experts found a longer average attention time on the minimap ($p > 1$); Experts focused more on the HP/Mana indicators ($p = 0.28$); Experts had a shorter average attention time on the shop button ($p = 0.27$) Experts demonstrated a higher number of gaze transitions. They required fewer revisits within the same AOI ($p < 0.001$)
Gotardi et al., 2019[29]	The study identified 4 AOIs: (1) race lane, (2) chronometer, (3) speedometer, (4) outside	The study did not provide any information	Fixation duration: No significant differences were observed in any area Number of fixations: Experts found a significantly higher number of fixations on the speedometer ($p = 0.021$). No significant differences were observed in the other AOIs ($p > 0.05$)
Bickmann et al., 2020[19]	The study identified 9 AOIs: (1) ball-carrying player, (2) next supporting player, (3) every other teammate (4) direct opponent of the ball-carrying player, (5) every other opponent player, (6) ball during pass or flank, (7) radar, (8) ball during shot on goal, (9) other fixation locations	Determined by manual assessment through direct inspection-methods	Fixation duration: Experts spent significantly less fixation duration on the areas corresponding to every other teammates ($p = 0.014$), while no statistically significant differences were observed in the other eight areas Number of fixations: Experts had a significantly higher number of fixations on the radar ($p = 0.010$). No significant differences were found in the other eight areas
Jeong et al., 2022[30]	The study identified 6 AOIs: (1) Mini-map with event alerts, (2) Enemy unit destruction and commander status, (3) Selected unit or building functions, (4) Resource count, (5) Active play zone view, (6) Total score from enemy destruction	The study did not provide any information	Fixation duration: Mini-map with event alerts: Experts exhibited longer fixation durations($p < 0.001$) Selected unit or building functions: Experts exhibited longer fixation durations($p = 0.02$). No difference in other areas
Jeong et al., 2024[14]	The study identified 4 AOIs: (1) status of the character controlled by participants (i.e., skill cooldown time and remaining health points), (2) mini-map showing the overall flow of the task, (3) main play area of the task, (4) play time and score	An AOI was identified for each fixation location based on the task interface utilized in the current experiment	Percentage of fixations: No significant differences were observed in any area
Wang et al., 2024[31]	The study identified 6 AOIs: (1) ball-carrying player, (2) next supporting player, (3) anticipation route, (4) football, (5) mini-map, (6) empty spaces	Defined by experts in the field of eSports	Number of fixations: Expert eSports players mainly fall in four areas: the ball-carrying player, the anticipation route, the next supporting player, the mini-map. Non-expert eSports players mainly fall in two areas: the football, the empty spaces (refer to an invalid pass path)
Joyce et al., 2024[32]	The study identified 4 AOIs: (1) lap time display, (2) circuit map, (3) in-car information screen, (4) tyre and brake temperature display, (5) speedometer, (6) the whole view outside the car (track)	The study did not provide any information	Percentage of fixations: Highly skilled simulated race car drivers spent a smaller proportion of their gaze time on the track ($p = 0.003$) Other AOIs not described

Table 3. Characteristics of AOI for inclusion in the studies.

all AOIs showed statistically significant differences. Overall, expert eSports players employed more targeted visual strategies that allowed for more efficient acquisition of key information and improved decision-making performance.

Saccade and first fixation duration

One study reported characteristics of saccades, but the data were not sufficient for meta-analysis[30]. The results showed that expert eSports players had significantly higher saccade velocity compared to non-experts ($p = 0.02$). Furthermore, experts showed a higher number of saccades than non-experts ($p = 0.005$). No significant differences in saccade length were found between the two groups.

One study evaluated the first fixation duration, but the data were insufficient for a meta-analysis[31]. The results showed a significant difference in first fixation duration between experts and non-experts ($p < 0.05$). Expert eSports players exhibited shorter first fixation duration.

Although the current evidence is limited, these findings suggest that saccade and first fixation duration may serve as key indicators for distinguishing between skill levels. Further research with larger samples is needed to confirm their generalizability.

Sensitivity analysis

In this study, a leave-one-out method was used to assess the impact of each study on the overall results of the meta-analysis. In this approach, each study was removed one at a time and the analysis was then rerun. The results showed that the significance levels of the overall analysis remained largely unchanged, even after excluding a single study. This suggests that the meta-analysis results in this study are robust.

Discussion

To our knowledge, this is the first systematic review and meta-analysis of eye movement characteristics of players in eSports. The aim of the study is to examine the differences between eSports players of different skill levels, with the aim of providing a more comprehensive understanding to improve players' performance in the game. To confirm potential differences, we systematically evaluated the average fixation duration and average number of fixations over the whole trial, as well as the eye movement characteristics within AOIs. The study revealed three key findings. First, expert eSports players had significantly shorter average fixation durations over the whole trial compared to non-experts ($P<0.05$). Second, there was no significant difference between expert and non-expert eSports players in the average number of fixations over the whole trial. Finally, our AOIs analysis showed that expert eSports players devoted more time and attention to relevant AOIs.

Our findings were compared with two meta-analyses related to eye movement characteristics in traditional sports athletes, and some differences were identified. A 2022 meta-analysis examined the differences in visual search strategies between expert and non-expert athletes in traditional sports. The study results showed no significant differences between expert and non-expert athletes in average fixation duration and average number of fixations[33]. Another meta-analysis examined the differences in visual search strategies between experts and non-experts in combat athletes. The results showed that expert athletes had a lower average number of fixations compared to non-expert athletes, while there was no significant difference in their average fixation duration[34]. Compared to the above studies, our research identified distinct results in the context of eSports. This discrepancy may reflect differences in eye movement characteristics between eSports and traditional sports. These differences may be due to the following factors: Traditional sports take place in real-world environments, where athletes are required to perform dynamic visual searches in complex and often unpredictable settings. In contrast, eSports is confined to a two-dimensional screen environment, demanding that players maintain a high level of attentional focus on processing information displayed on the screen[35]. Second, differences in study design and measurement metrics between the included research papers may have affected the comparability of the results. It is important to note that research on eye movement characteristics in eSports is still in its early stages and only a limited number of studies are currently available. Therefore, the specific causes of these differences remain uncertain. This result should be interpreted with caution and we recommend conducting larger and more rigorous studies in the future to investigate the underlying mechanisms underlying these differences.

This study found thatexpert eSports players exhibited shorter average fixation durations over the whole trial. This can be attributed to different levels of perceptual-cognitive expertise[36] with the ability to quickly acquire visual information considered crucial for high-level performance, particularly in sports[37,38]. More effective visual search strategies allow expert eSports players to quickly capture important information on the screen without prolonged fixations on a single object. In contrast, non-expert eSports players often struggle to rapidly locate and utilize information from visual stimuli, resulting in longer fixation durations and lower information processing efficiency. This explanation is also supported by existing research. For example, Rayner (1998) found that experts can acquire more information and make more effective decisions through brief fixations. This suggests that shorter fixation durations are sufficient to complete tasks[39]. Additionally, another study found that expert eSports players can predict dynamic changes in the game more accurately, reducing unnecessary fixation duration[40]. The long-term working memory theory provides a potential explanation for how experts quickly acquire information. This theory posits that experienced gamers can encode and retrieve information more rapidly, enabling them to make decisions and respond more quickly.

Surprisingly, there was no significant difference between expert and non-expert eSports players in the average number of fixations over the whole trial. Due to higher visual search efficiency, experts are typically expected to have fewer fixations. However, it is important to note that video games often feature very dynamic and complex scenes that require players to continually adapt to the changing environment. Previous research has shown that visual clutter can negatively impact performance and alter visual behavior during visual search in gaming scenarios. Under high-clutter conditions, experts actually exhibited an increased number of fixations[41].

Meanwhile, non-professional players have difficulty identifying relevant information, leading to disorganized fixations. These factors may have, to some extent, attenuated the differences in fixation count between expert and non-expert players, thereby helping to explain the findings of the present study. Furthermore, we observed high heterogeneity ($I^2 = 78\%$). This high heterogeneity may be due to differences in the type of stimuli used across studies. Mann et al. (2017) found that stimulus type is an important moderating variable in the expert/non-expert research paradigm in the field of perceptual-cognitive[36]. In eye tracking experiments, the type and complexity of the stimulus materials significantly influence fixation behavior. If there are uncontrolled differences between stimuli in terms of visual or cognitive factors, the eye movement data may be confounded by these variables[17,42]. Related research has also confirmed that static stimuli and dynamic scene stimuli produce different fixation patterns in visual search, further highlighting the potential impact of stimulus type on the consistency of research results[36]. Wang et al. (2024) used a simulated stimulating environment (FIFA 21 screenshots), while other studies employed a realistic stimulating environment. When conducting a subgroup analysis based on stimulus type and excluding Wang et al. (2024), the heterogeneity was significantly reduced to 0. We therefore conclude that differences in stimulus type are the main cause of the high heterogeneity observed across studies.

Our results also showed differences in fixation duration and number of fixations on areas of interest (AOIs) among eSports players of different skill levels. In other words, expert eSports players tend to pay more attention to certain AOIs. This suggests that experts are more adept at selectively allocating their attention to identify and prioritize key areas in the game, which is crucial in eSports. The information reduction hypothesis provides a theoretical framework to explain this phenomenon[43]. The theory posits that expert players have the ability to filter out irrelevant information and focus only on data directly impacting the current task or decision. This capability enables expert players to use their limited cognitive resources more efficiently, allowing them to respond quickly and accurately in rapidly changing game environments.

The results of this meta-analysis have practical implications. First, by using systematic review and meta-analysis methods, it summarizes the results of multiple studies, thereby increasing the reliability and validity of the conclusions. Second, this research can provide a scientific basis for optimizing eSports training methods. While existing studies have examined various factors that may influence eSports performance, the key determinants of gaming performance remain unclear[13]. Our study also identifies specific eye movement characteristics associated with high-level gaming performance and provides insights for optimizing gaming performance. For example, professional eSports players typically exhibit shorter fixation durations and demonstrate more efficient visual search strategies. These findings can be directly applied to training and help players optimize their visual attention allocation. Finally, this study also provides new metrics for the selection and evaluation of eSports players. Traditional selection and evaluation methods are based primarily on player performance and experience, but these approaches may not fully capture a player's potential and true abilities. By incorporating eye movement features into the analysis, we can more objectively assess players' visual cognitive abilities and reaction times, thereby improving scientific accuracy and precision in the selection of professional eSports players.

However, this study has several limitations. First, potential selection bias (such as language bias and publication bias) may lead to biased results, as this study only included peer-reviewed articles published in English, thereby overlooking some valuable non-English and grey literature. To enhance the comprehensiveness of the research, future studies should broaden the scope of literature search to include research findings in multiple languages. Second, the generalizability of the findings may be constrained by variations in experimental design, particularly the lack of standardized protocols for stimulus presentation and game genre selection. To enhance the external validity of research conclusions and mitigate heterogeneity-induced bias, future studies should establish stricter operational guidelines during experimental paradigm design, with particular emphasis on standardizing critical parameters such as stimulus presentation methods and task requirements. Third, the absence of blinding in the included studies may lead to observer bias or detection bias. In the design phase, future studies should explicitly adopt single-blind, double-blind, or triple-blind strategies to improve the accuracy and reliability of the research findings. Finally, future research could consider adopting longitudinal or repeated measures designs to further explore how eye movement evolve with training.

Conclusion

In summary, this systematic review and meta-analysis provides a comprehensive comparison of eye movement characteristics between professional and non-professional eSports players and provides empirical support for eSports training and performance improvement. As the eSports industry continues to evolve, a deeper understanding of players' visual behavior will play a critical role in improving competitive performance.

Data availability

All data generated or analyzed during the current study available from the corresponding author on reasonable request.

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Conceptualization: LYK and SJC; Literature search: LYK, CYH and CJH; Quality assessment: YCL, CYH and CJH; Data extraction: YCL, CYL and CJH; Data analysis: LYK and SJC; LYK wrote the manuscript draft; LYK, SJC revised the manuscript. All authors reviewed and approved the final manuscript.

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