Research Article RJ-60

Researches on Multidisciplinary Approaches 2026 (3), 1-14 ISSN:2791-9099

Evaluating Valorant Player Experience through Psychophysiological Data Harvesting

Neslihan Erdem / Res. Asst. Dr.
Aydın Adnan Menderes University, Faculty of Communication, Department of Visual Communication Design
neslihan.erdem@adu.edu.tr

Yaren Demirel / Lect.
Fatih Sultan Mehmet Vakif University, Vocational School, Department of Visual Communication
ydemirel@fsm.edu.tr

Sumru Yıldırım / Asst. Prof. Dr.
Aydın Adnan Menderes University, Faculty of Communication, Department of Radio, Television and Cinema
sumruyildirim@adu.edu.tr

Behiç Alp Aytekin* / Prof. Dr.
Aydın Adnan Menderes University, Faculty of Communication, Department of Visual Communication Design
alpaytekin@adu.edu.tr

*Corresponding Author

Abstract

This study examines the visual attention distributions and physiological responses of Valorant players across different expertise levels using the Psychophysiological Data Harvesting (PDH) technique within a cross-sectional, quasi-experimental, between-groups laboratory design. Within standardised gameplay scenarios designed through the Wizard of Oz (WoZ) technique, eye-tracking and electrodermal activity (EDA) measurements were collected alongside pre- and post-tests. Participants were classified into three expertise groups (novice, competent, and expert; n = 10 per group) based on Riot Games' official ranking system and the novice-to-expert model proposed by Dreyfus and Dreyfus (1980). Between-group comparisons were conducted using the Kruskal-Wallis test, with corresponding effect sizes presented alongside descriptive statistics. Descriptive patterns emerged across the eye-tracking and EDA measures: novice players allocated the highest proportion of visual attention to the central game area, whereas expert players showed a descriptively higher proportion of fixations on the map area of interest; competent players exhibited the highest mean skin conductance values, followed by expert and novice players. None of the between-group comparisons of the psychophysiological measures were statistically significant, and the observed effect sizes were small. In line with the study's aim of demonstrating the systematic application of an integrated psychophysiological data-collection procedure, these descriptive patterns and effect-size estimates are presented as reference values for the sample-size planning of subsequent confirmatory research. The methodological contribution lies in the integrated application of eye-tracking, EDA, WoZ, and pre- and post-test procedures within the PDH framework to jointly interpret quantitative psychophysiological and qualitative data.

Keywords: Player Experience, Eye-tracking, Electrodermal Activity, Psychophysiological Data Harvesting, Wizard of Oz.

JEL Codes: L82, L86

Citation: Erdem, N., Demirel, Y., Yıldırım, S., & Aytekin, B. A. (2026). Evaluating Valorant player experience through psychophysiological data harvesting. *Researches on Multidisciplinary Approaches (ROMAYA Journal)*, 2026(3), 1-14

Submission Date : 07.04.2026
Acceptance Date : 05.10.2026

1. Introduction

Esports, which has developed rapidly in recent years, has become a significant area of study attracting the interest of researchers from various disciplines (Hindin et al., 2020; Hedlund, 2023; Martins et al., 2022; Cheng et al., 2023; Riedl & Verschuuren, 2025). Digital games, which form the foundation of the esports ecosystem, aim to provide players with enjoyable and satisfying experiences. However, this experience varies depending on players' individual characteristics and their level of competitive expertise. Consequently, investigating the player experience in digital games represents a critical need from both academic and industry perspectives.

Esports is a competitive field encompassing various genres, such as multiplayer online battle arena (MOBA), first-person shooter (FPS), real-time strategy (RTS), sports games, and card games (Bányai et al., 2019). In the context of human-computer interaction, players compete individually or in teams within the rules of the game and develop increasingly complex strategies (Thiel & John, 2018). Competitive games have rapidly gained global popularity both for playing and spectating (Kamal & Saeed, 2025). By 2025, the global esports audience had exceeded 640 million, with at least 50% of that audience being regular viewers (Statista, 2025). This development illustrates that esports has evolved from a form of entertainment into a global media and communication platform.

Despite the growth of the sector, the number of studies examining the esports player experience through psychophysiological indicators in relation to competitive expertise remains limited. In particular, the joint examination of visual attention patterns and physiological arousal in competitive FPS games points to a research gap that a more holistic account of the player experience could help to address. Building on this gap, the present study examines the experiences of Valorant players who use the PDH technique in a cross-sectional, quasi-experimental, between-groups laboratory design. Eye-tracking and EDA measurements were collected during five standardised game rounds designed with the WoZ, a procedure in which certain aspects of the interactive environment are controlled by the researcher without the participants' awareness in order to standardise the stimulus flow across participants- and were complemented by pre- and post-test procedures.

The primary aim of the study is not to establish confirmatory evidence of expertise-related differences but to demonstrate the systematic application of an integrated psychophysiological data-collection procedure that combines quantitative and qualitative measures, and to generate descriptive patterns and effect-size estimates that may guide the design of subsequent psychophysiological research procedures in esports. Within this framework, the research addresses the following questions:

RQ1: How are competitive expertise levels (novice, competent, expert) associated with esports players' visual attention patterns and physiological arousal?

RQ2: How is competitive expertise level associated with the distribution of players' visual attention across the game interface?

In the following section, previous studies on the esports ecosystem, player experience, and Valorant are reviewed in order to establish the theoretical and empirical foundation of the present study.

2. Literature Review

2.1. The Esports Ecosystem

With the widespread adoption of digital technologies, online competitive gaming has evolved into a global professional ecosystem, known as esports, in recent years (Rahmawati et al., 2019, p. 41). Esports is a competitive field based on electronic games that requires a high level of strategic planning and team coordination. Today, esports has moved beyond merely a form of digital entertainment to a competitive arena examined through the lens of sports science, given its performance-based structure and training processes. In this context, esports is regarded as a multidimensional phenomenon that warrants investigation across player experience, human-computer interaction, and cognitive and psychophysiological processes.

Among esports disciplines, first-person shooter (FPS) games, in particular, stand out for their competitive structures that require players to develop skills such as rapid decision-making, situational awareness, and strategic attention management (Yang et al., 2025). Examining differences in visual attention patterns and psychophysiological responses across expertise levels in such games contributes to understanding the cognitive processes associated with competitive esports. Therefore, examining visual attention and physiological responses across expertise levels represents an important area of research for understanding competitive gameplay.

2.2. Player Experience

Player experience encompasses the cognitive, emotional, and behavioral responses that arise during the interaction between the player and the game (Wiemeyer et al., 2016; Denisova & Cairns, 2015). Studies on players' motivations in esports indicate that factors such as competition, challenge, entertainment, and socialization shape the player experience (Hamari & Keronen, 2017; Hedlund, 2023; Mangat et al., 2025). However, competitive esports

has been associated with strategic thinking, rapid decision-making, and psychological resilience (Himmelstein et al., 2017, p. 12).

Concepts such as usability, user experience, and playability provide an important framework for evaluating the player experience (Rienzo & Cubillos, 2020; Nacke, 2015, p. 67). However, such conceptual evaluations often rely on subjective reports to explain players' experiences and remain limited in their ability to directly capture the cognitive-emotional processes that arise during gameplay. Accordingly, integrating psychophysiological measures, such as eye-tracking and electrodermal activity, with self-report data may provide a more comprehensive understanding of the player experience.

2.3. The Valorant Game and Research Context

Valorant is a team-based competitive first-person shooter (FPS) multiplayer digital game released by Riot Games in 2020 (Webster, 2020). As one of the most widely played competitive FPS games in Türkiye (Gaming in Turkey, 2020), Valorant provides an appropriate context for investigating competitive esports because its gameplay relies heavily on visual attention, rapid decision-making, and physiological adaptation to dynamic game situations, making it well-suited for eye-tracking and EDA research.

The limited number of studies on the Valorant player experience have revealed that the game's visual interface offers a strong user experience, yet certain design elements can pose challenges for new players (Diass et al., 2022; Aisyah, 2023). However, psychophysiological research on how visual attention patterns and physiological arousal levels vary with skill level in FPS games such as Valorant remains limited. Therefore, the present study aims to examine visual attention patterns, physiological responses, and self-report data across different levels of competitive expertise in Valorant using the PDH framework.

3. Methods

3.1. Sample and Data Collection

Although existing studies have shed light on the psychophysiological effects of digital games (Drachen et al., 2010; Vasiljevic & Miranda, 2020; Wang et al., 2022), research examining visual attention patterns and physiological responses across esports expertise levels remains limited. In particular, few studies have compared players with varying levels of competitive expertise under controlled laboratory conditions, using integrated eye-tracking and EDA measurements.

In this study, a cross-sectional, quasi-experimental, between-groups laboratory design was employed to investigate how competitive expertise in Valorant is associated with players' visual attention patterns and physiological arousal (Shadish et al., 2002). Because expertise could not be randomly assigned, participants were grouped according to the competitive rank they had attained rather than being subjected to an experimental manipulation. The study adopted a multidimensional design combining quantitative and qualitative data collection methods and was based on the PDH technique (Aydın et al., 2021; İcil Tuncer et al., 2023). Accordingly, eye-tracking, EDA, the WoZ, and pre- and post-test applications were integrated to provide complementary sources of data. The integrated interpretation of these quantitative psychophysiological measures and qualitative findings constitutes the study's primary methodological contribution.

PDH is not a method but a systematic research technique: it integrates conventional qualitative and quantitative data-collection instruments with psychophysiological measurement tools in a manner aligned with the nature of the research. What distinguishes PDH from ordinary multimodal data collection is its principle of procedural flexibility and integrative interpretation: the choice of psychophysiological instruments, as well as the structuring of pre- and post-test procedures, is determined by the research question and context, and the instruments are not merely applied in parallel but are structured so as to complement and mutually inform one another. This framework comprises three main stages: (i) preparatory and contextual data collection, in which participant characteristics, experiences, and motivations are identified through the pre-test procedures required by the research; (ii) concurrent psychophysiological measurement, in which the measurement tools selected according to the nature of the research (in this study, eye-tracking and EDA) are applied concurrently during stimulus presentation; and (iii) integrative cognitive-response collection, in which participants' experiences are elicited retrospectively through the post-test procedures required by the research and interpreted together with the quantitative data (Aydın et al., 2021; İcil Tuncer et al., 2023).

The study's participants were players of varying levels of expertise who actively play Valorant, an online first-person shooter widely played in Türkiye. Because no established effect sizes are available for eye-tracking and EDA differences across competitive expertise levels in Valorant, the target sample size was determined based on methodological recommendations for eye-tracking research rather than an a priori power analysis. Holmqvist et al. (2011, pp. 133), a standard reference in eye-tracking methodology, recommend a minimum of 10 participants per experimental cell as a practical benchmark for publication-quality research. This recommendation continues to be reflected in contemporary eye-tracking studies, in which similar sample sizes are commonly

reported for investigations of gaze behavior and psychophysiological responses during gameplay (Tammi et al., 2025; Cowley et al., 2014b). In addition, Pernice and Nielsen (2009) recommend approximately six participants for qualitative eye-tracking studies and around 30 participants for quantitative heatmap analyses. The target sample size of 10 participants per expertise group, therefore, falls within these methodological recommendations.

Data collection was carried out between April and May 2024. The study received approval from the Social and Human Sciences Research Ethics Committee of the affiliated institution. A total of 30 players were recruited, and no participants were excluded from the study. For seven participants, the initial eye-tracking calibration did not meet the required accuracy threshold due to head movements; calibration was repeated until acceptable quality was achieved. In the competent group, one participant experienced partial detachment of the EDA electrode during gameplay, resulting in a galvanic skin response (GSR) value outside the physiological range (-11.92 µS). The participant's eye-tracking and skin conductance response (SCR) data were retained for analysis, whereas the mean GSR value was excluded from the corresponding analysis. The final sample comprised 30 players (10 women and 20 men), with 10 participants in each expertise group (Table 1).

Table 1. Descriptive Characteristics of Participants by Expertise Group

Characteristic	Novice (n = 10)	Competent (n = 10)	Expert (n = 10)
Age (years), M (SD)	22.4 (1.6)	20.7 (1.6)	20.7 (1.4)
Age range	19-24	19-24	19-24
Gender (male / female)	9 / 1	7 / 3	4 / 6
Rank group	Iron-Bronze-Silver	Gold-Platinum	Diamond-Ascendant-Immortal-Radiant
Valorant experience (years), M (SD) [a]	4.0 (1.4)	3.4 (1.5)	2.7 (1.7)
Weekly playing time (hours), M (SD) [b]	23.8 (13.8)	23.8 (12.5)	32.2 (13.8)

Note. Rank was reported at the group-tier level, corresponding directly to the expertise classification used in the analysis. Peak competitive rank and FPS gaming experience beyond Valorant were not collected as structured survey items and are therefore not reported.

[a] Reported using ordinal response categories (<1 year, 2–3 years, 4–5 years, 5+ years); values shown are estimated using category midpoints.

[b] Estimated from daily playing time (self-reported in categories: 1-2, 3-4, 4-5, 5-6, 6-7, 7+ hours per day) multiplied by 7; values shown use category midpoints.

Players were divided into three groups based on Riot Games' official competitive ranking system and on Dreyfus and Dreyfus's (1980) Novice-to-Expert model. Although the original Dreyfus model describes skill acquisition as a five-stage process, the present study operationalized expertise using three functional categories (novice, competent, and expert) to better reflect Valorant's competitive ranking structure and to enable meaningful between-group psychophysiological comparisons. Specifically, the novice group comprised players in the Iron, Bronze, and Silver leagues; the competent group included players in the Gold and Platinum leagues; and the expert group consisted of players in the Diamond, Ascendant, Immortal, and Radiant leagues (Riot Games, 2026). This grouping is consistent with Valorant's competitive segmentation while preserving the broader theoretical progression of expertise described by Dreyfus and Dreyfus (1980). Similar operationalizations that collapse the five Dreyfus stages into broader functional categories have also been adopted in previous skill acquisition research (Cowley et al., 2012).

Each session lasted approximately 30-60 minutes. A Tobii Fusion screen-based eye-tracking device (60 Hz sampling rate) was used for eye-tracking measurements, whilst a Shimmer GSR+ device (128 Hz sampling rate) was used for electrodermal activity measurements. For EDA recording, electrodes were placed on the index and middle fingers of the participants' non-dominant hand and on the earlobe. Data streams from both devices were synchronised in Tobii Pro Lab (v. 1.181).

Participants were seated approximately 55-65 cm from the display and positioned at an angle of approximately 90° relative to the monitor. At the start of each session, the eye-tracking device was calibrated using a nine-point procedure on a uniform gray background, and calibration quality was evaluated with Tobii Pro Lab's built-in validation procedure. Recordings were accepted only when a minimum calibration quality of 90% was achieved, corresponding to the accuracy recommendations reported by Holmqvist et al. (2011, pp. 132-134).

In the first phase of the procedure, participants' demographic information, Valorant ranks, gaming

frequency, and motivations were collected via pre-test questions. Additionally, the roles adopted by the players, their communication channels, and their tendencies towards team play were investigated.

The gaming sessions were conducted using the WoZ technique. Participants were informed that they would experience a natural competitive Valorant match, while the research team covertly controlled team composition to ensure that each participant played alongside teammates of comparable expertise. This approach enabled the standardisation of the experimental conditions while preserving a natural gameplay experience (Dahlbäck et al., 1993).

Each game session involved one participant and four confederates forming a five-player team and entering Valorant's online matchmaking system together. The opposing team consisted of players randomly assigned by Valorant's matchmaking algorithm. To ensure age compatibility, the confederates were between 21 and 24 years old and had between two and five years of Valorant experience. The same confederates maintained the same roles throughout all sessions, with no role rotation. Participants played in the laboratory using a 24-inch Full HD (1920×1080) monitor with a 75 Hz refresh rate and a headset, whereas the confederates participated from a separate room.

All sessions were conducted using Valorant Episode 8 (Acts 2-3). The map for each session was randomly assigned by the game's matchmaking system. Participants played on both the Attacker and Defender sides, agent selection was unrestricted, and in-game voice communication among teammates was permitted. Each session was limited to five rounds, and participants were informed of this limit before the experiment. At the conclusion of the fifth round, the confederates ended the match using Valorant's in-game surrender mechanism. The five-round limit was established to minimize the risk of signal degradation, electrode displacement, and participant fatigue during prolonged EDA recording. Following each session, participants were fully debriefed regarding the WoZ procedure, including the role of the confederates and the controlled team composition, and were given the opportunity to ask questions.

Following the gameplay session, participants completed the post-test questionnaire, which was identical in structure to the pre-test questionnaire. The questionnaire employed a mixed-format design consisting of closed-ended questions on participants' demographic characteristics and gaming habits (e.g., age, gender, Valorant experience, weekly playing time, competitive expertise level, preferred agent role, communication channel, and pre-game preparation routine), together with open-ended questions exploring gameplay motivation, visual attention strategies, interface elements that attracted attention during gameplay, decision-making strategies, team dynamics, in-game communication, and perceived performance. The questionnaire was designed in accordance with the PDH framework (Aydın et al., 2021; İcil Tuncer et al., 2023). The open-ended responses were used as supportive contextual data to facilitate the interpretation of the eye-tracking and EDA findings rather than as primary analytical data. Accordingly, no formal coding procedure or inter-coder reliability analysis was conducted. Instead, the responses were reviewed by the research team and used to contextualize the quantitative psychophysiological findings.

3.2. Data Analysis

Raw gaze data were processed in Tobii Pro Lab using the Velocity-Threshold Identification (I-VT) fixation filter (Salvucci & Goldberg, 2000). The software's default velocity threshold of 30°/s was used to distinguish fixations from saccades, and the minimum fixation duration was set to 60 ms, consistent with common practice in the eye-tracking literature (Holmqvist et al., 2011). Calibration repetitions performed during data collection were not included in the analyses. Gaze data quality was continuously monitored throughout each recording session, and a track-loss threshold of 15% was predefined as an exclusion criterion; no recording exceeded this threshold. Gameplay intervals were manually defined in Tobii Pro Lab, and all gaze analyses were restricted to these intervals.

The raw EDA signal was analysed synchronously with the eye-tracking data in Tobii Pro Lab and, following Boucsein (2012), decomposed into a tonic component (Skin Conductance Level; SCL), representing general arousal level, and a phasic component (Skin Conductance Response; SCR), reflecting short-term responses. Artifact detection was performed within Tobii Pro Lab, and sessions with signal loss exceeding 15% were excluded from analysis. Although no separate resting-baseline protocol was administered prior to data collection, the Valorant loading procedure lasted on average 5-8 minutes at the start of each session. During this window, both the Shimmer GSR+ and Tobii Pro Lab continued to record, providing a naturalistic adaptation baseline that allowed participants to physiologically acclimate to the devices and the laboratory environment (Boucsein, 2012; Cowley et al., 2014a). Session duration from game onset was marked as an interval in Tobii Pro Lab, and only in-game data were used in the analyses.

Two distinct EDA measures were presented. Total SCR count was defined as the sum of skin conductance responses observed in the phasic component throughout the session and was used as an index of overall physiological reactivity. ER-SCR (Event-Related Skin Conductance Response) was operationalised differently because the Valorant environment presents a continuous, multi-component stimu-

lus stream, making time-locking to specific in-game events infeasible. Instead, following Boucsein (2012), suprathreshold sudden rises in the phasic component (≥0.01 µS) were classified as ER-SCRs, with a response window of 1-4 seconds; overlapping responses within this window were treated as a single ongoing response. The observed ER-SCR counts (novice: n = 2; competent: n = 3; expert: n = 0) were insufficient for inferential comparison and are therefore reported as supporting case-level observations.

Total session duration across the five-round protocol varied across participants (novice: M = 1048.82 s, SD = 229.53; competent: M = 969.53 s, SD = 187.54; expert: M = 908.34 s, SD = 132.44). A Kruskal-Wallis test (Kruskal & Wallis, 1952) confirmed that this difference was not statistically significant (H = 3.169, p = 0.205). Nevertheless, to control for session-length variability, all count-based measures were normalised per minute (fixations per minute, SCRs per minute). AOI-based total fixation durations were normalised to the total recording time and expressed as percentages, an approach that simultaneously controls for session-duration differences and for confounding introduced by disparities in AOI size.

Six Areas of Interest (AOIs) were defined on the basis of the fixed elements of the Valorant heads-up display (HUD): the map AOI, team information AOI, ability bar AOI, combat report AOI, action notifications AOI, and game area AOI (see Figure 1). Each AOI corresponded to a functionally distinct region of the HUD conveying a specific class of tactical information. The map AOI, located in the upper-left corner of the screen, contained a mini-map displaying the current map layout, teammate positions, detected enemy pings, and recent gunfire indicators; it served as the primary source of spatial-tactical awareness. The team information AOI, positioned along the upper-left edge below the map, displayed teammate identifiers, health values, ultimate ability status, and equipped weapons, providing continuous updates on the team's state. The ability bar AOI, located in the lower-left region of the screen, displayed the player's own agent abilities, remaining charges, and cooldown states, and thus reflected access to ability-related information. The combat report AOI, positioned in the upper-right corner, occupied a spatially fixed screen location while its content updated dynamically during combat events, presenting kill notifications, damage exchanges, and elimination feed entries. The action notifications AOI, located in the lower-central region above the ability bar, contained context-dependent action prompts such as spike-plant/defuse cues, weapon-purchase notifications, and interaction indicators. Finally, the game area AOI encompassed the central three-dimensional gameplay viewport, in which enemy detection, aiming, movement, and moment-to-moment decision-making occur.

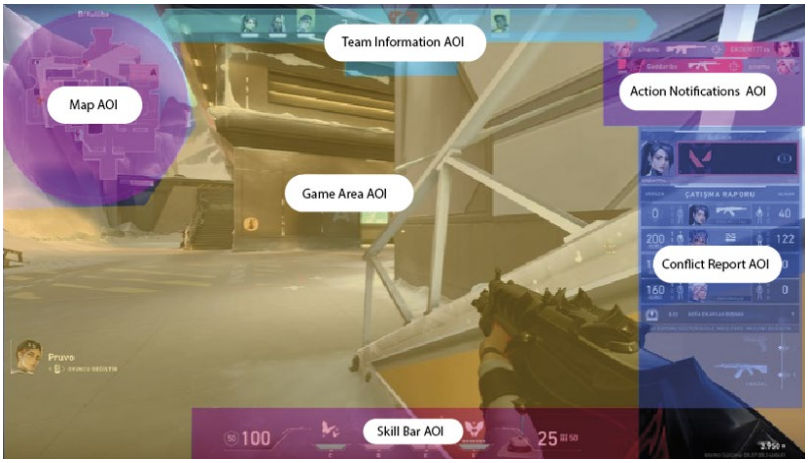


Figure 1. Areas of Interest (AOIs) in the Valorant Interface

Note. In some Valorant interfaces, the ability bar is labeled "skill bar"; the two terms refer to the same interface element.

AOI boundaries were specified using pixel coordinates in Tobii Pro Lab and were validated by an expert review panel comprising five members- two Immortal-ranked competitive players, one game designer, and two eye-tracking researchers- who provided independent judgments. Only regions on which all panel members reached consensus were retained in the final AOI set. Five of the six AOIs (map, team information, ability bar, action notifications, and game area) remained spatially fixed throughout gameplay; the combat report AOI likewise occupied a fixed screen location while its content updated dynamically during combat events. Because AOI boundaries were held constant, changes in interface content did not affect AOI definitions. The approximate screen-area proportions of the six AOIs were as follows: game area AOI ~65-70%, map AOI ~8-10%, ability bar AOI ~6-7%, team information AOI ~5-6%, combat report AOI ~5-6%, and action notifications AOI ~4-5%. Although this size disparity is acknowledged,

per-pixel normalisation was not applied because the study aimed to characterise the absolute distribution of players' visual attention across HUD elements; interpretations are therefore grounded in relative distributional patterns across groups rather than in area-adjusted values. Participants' visual attention within these areas was assessed using average fixation duration (FD), fixation count (FC), and visit count (VC), and comparisons were made across the three expertise groups.

Group comparisons were conducted using the Kruskal-Wallis non-parametric test (Kruskal & Wallis,1952). This choice was motivated by three considerations: (i) the small per-group sample size (n = 10), (ii) violations of the normality assumption for several variables, and (iii) the cross-sectional, quasi-experimental design of the study. To support sample-size planning in subsequent confirmatory work, effect sizes (η^2) and 95% confidence intervals are presented alongside test statistics (Cohen, 1988).

4. Results

This section presents psychophysiological findings obtained from Valorant players at different skill levels (novice, competent, expert). The findings are presented based on pre-test and post-test data, along with eye-tracking and EDA measurements collected within Areas of Interest (AOIs) defined on the game interface. Consistent with the cross-sectional, quasi-experimental, between-groups laboratory design of the study, all between-group comparisons for continuous physiological and gaze measures were conducted using the Kruskal-Wallis test, together with corresponding effect sizes (η^2) intended to inform sample-size planning in subsequent research procedures. Pre-test and post-test descriptive responses are presented as percentages without inferential testing.

4.1. Pre-test Findings

Pre-test responses suggest that players' pre-game preparation routines varied descriptively across skill levels. Among expert players, 4/10 (40%) reported adjusting their equipment, 4/10 (40%) reported organising their gaming environment, and 2/10 (20%) reported not undertaking any preparation. Among competent players, 6/10 (60%) reported adjusting their equipment, whereas among novice players, 5/10 (50%) reported only organising the environment, and 3/10 (30%) reported no pre-game preparation. Descriptively, these patterns are consistent with the possibility that players with higher self-reported skill levels attend more to optimising technical and environmental conditions before starting the game, although statistical comparisons were not conducted for these categorical responses (Figure 2).

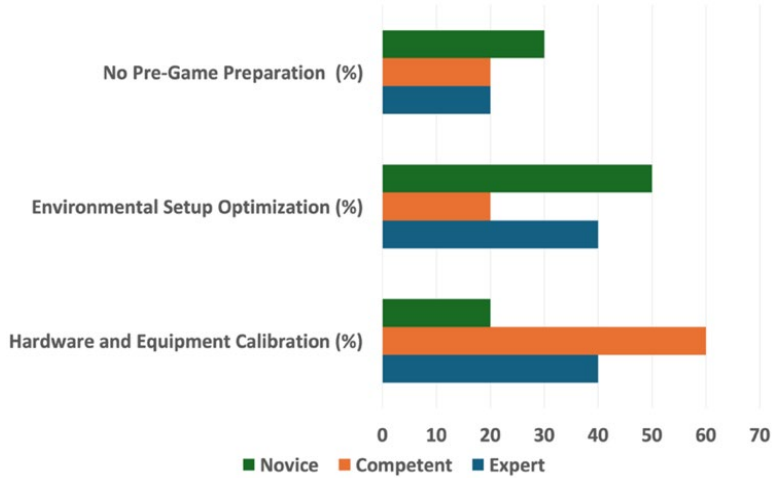


Figure 2. Distribution of Pre-Game Preparation Routines by Player Expertise Level

Descriptive patterns in reported training habits also varied across groups. Among expert players, 4/10 (40%) reported training regularly, whereas among novice players, 5/10 (50%) reported not training at all. These proportions are descriptively consistent with the possibility that regular practice becomes a more systematic component of gameplay routines at higher skill levels, although this observation is not supported by inferential testing (Figure 3).

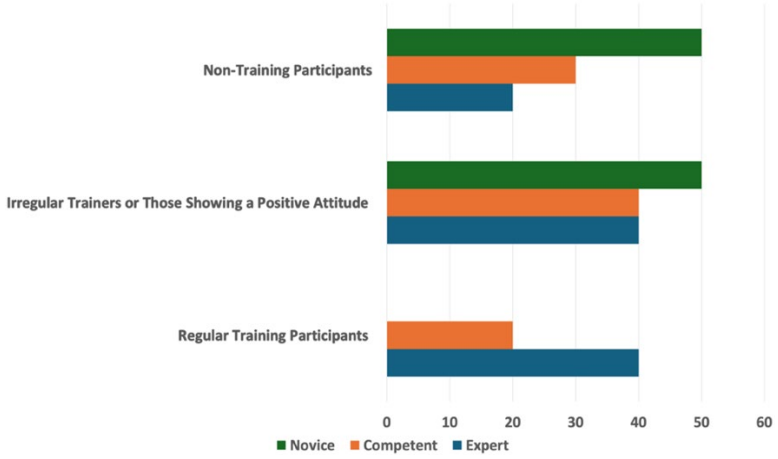


Figure 3. Training Habits and Attitudes by Player Expertise Level

4.2. Post-test Findings

Post-test responses regarding decision-making strategies also varied descriptively across expertise groups. Among expert players, 4/10 (40%) reported relying primarily on an intuitive playing style, whereas 5/10 (50%) of competent and 5/10 (50%) of novice players reported preferring a tactical/analytical approach. Descriptively, this pattern is consistent with theoretical accounts of skilled performance, which propose that extensive deliberate practice may enable decision-making to become increasingly rapid and experience-based (Ericsson & Kintsch, 1995); however, group-level inferences cannot be drawn from these descriptive proportions, and the pattern should be interpreted as a descriptive observation (Figure 4).

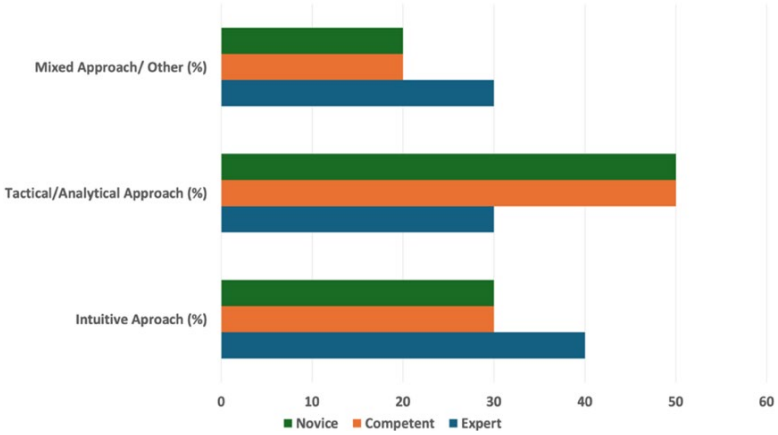


Figure 4. Decision-Making Strategies by Player Expertise Level

4.3. Eye-tracking Findings

Eye-tracking data reveal descriptive tendencies in players' visual attention distributions across expertise groups, although none of the between-group differences reached statistical significance (all $p > 0.10$; see Table 2). On the normalised total fixation duration measure, novice players allocated the highest proportion of visual attention to the game area (M = 30.57%, SD = 7.06), followed by expert (M = 27.91%, SD = 7.17) and competent players (M = 23.52%, SD = 10.64). On the map AOI, expert players showed the highest descriptive proportion (M = 3.89%, SD = 4.12) compared with novice (M = 2.65%, SD = 2.38) and competent players (M = 2.14%, SD = 1.84). These descriptive patterns are exploratory and should be interpreted as tendencies to be examined in a future confirmatory study.

Table 2. AOI-Based Normalised Total Fixation Duration Across Expertise Groups

AOI	Novice M % (SD)	Competent M % (SD)	Expert M % (SD)	H	p	η^2
Game Area	30.57 (7.06)	23.52 (10.64)	27.91 (7.17)	3.014	0.222	0.038
Map	2.65 (2.38)	2.14 (1.84)	3.89 (4.12)	0.266	0.876	-0.064

Ability Bar	0.78 (0.42)	0.51 (0.48)	0.51 (0.35)	3.507	0.173	0.056
Team Information	0.74 (0.38)	0.96 (0.68)	0.82 (0.48)	0.537	0.765	-0.054
Combat Report	0.68 (0.94)	0.40 (0.35)	0.41 (0.27)	0.560	0.756	-0.053
Action Notifications	0.29 (0.29)	0.15 (0.14)	0.28 (0.18)	2.516	0.284	0.019

Note. Values represent AOI fixation duration as a percentage of total recording time (AOI fixation duration ÷ total recording time × 100). Kruskal-Wallis tests were used for between-group comparisons (n = 10 per group; N = 30). Effect sizes are reported as $\eta^2 = (H - k + 1) / (N - k)$. Negative η^2 values indicate that observed between-group differences fell below the level of chance variation.

Pre-test responses provide contextual information that is broadly consistent with these observed distributions. In response to the multiple-choice question "What do you pay the most attention to during gameplay?", 17/30 (56.7%) of players across all expertise levels selected "map", and the eye-tracking data likewise indicated that, after the game area, the map AOI received the largest share of visual attention across groups.

Descriptively, competent players tended to allocate a slightly higher proportion of fixations to the team information AOI (M = 0.96%, SD = 0.68) than novice (M = 0.74%, SD = 0.38) or expert players (M = 0.82%, SD = 0.48), although this pattern was not statistically significant (H = 0.537, p = 0.765, $\eta^2 = -0.054$). One possible interpretation- to be examined in future work- is that competent players, whose gaming experience is developing but who have not yet reached expert-level automaticity, may attend more to team-related information; however, this remains a hypothesis rather than a confirmed finding.

Novice players showed a numerically higher proportion of fixations on the ability bar AOI (M = 0.78%, SD = 0.42) than competent (M = 0.51%, SD = 0.48) or expert players (M = 0.51%, SD = 0.35), but this difference was not statistically significant (H = 3.507, p = 0.173, $\eta^2 = 0.056$). The ability bar contains fundamental interaction information such as ability shortcuts, ammunition status, and health, which may be more actively monitored by players who have not yet automated basic game mechanics. Prior work has suggested that experiential learning enables interaction with such interface elements to become increasingly reflexive over time (Luo et al., 2025); the present descriptive pattern is broadly consistent with this account but requires confirmatory testing with larger samples.

In terms of variability, standard deviations across all AOIs remained comparable across groups, and no systematic difference in within-group dispersion emerged from the current data.

Qualitative responses collected during the post-test interviews provide contextual illustrations that are broadly consistent with the observed distributions. For instance, one expert participant (P4) noted: "Because I continuously monitor the map, I do not need to look at the team information." Such statements are offered as individual-level illustrations rather than as evidence of group-level effects; interpretations of the relationship between AOI use and expertise remain exploratory and would require larger-sample confirmatory studies.

4.4. Electrodermal Activity Findings

Descriptively, mean skin conductance (GSR) values differed across groups: competent players showed the highest mean value (M = 10.57 µS, SD = 6.90), followed by expert (M = 7.89 µS, SD = 5.12) and novice players (M = 7.13 µS, SD = 4.00). However, this between-group difference was not statistically significant (H = 1.621, p = 0.445, $\eta^2 = -0.015$; see Table 3). Because the between-group differences did not reach significance, group-level inferences regarding cognitive load, arousal regulation, or the automatisation of information processing cannot be drawn from these data. Prior theoretical accounts have proposed that intermediate-level performers may experience elevated cognitive load as they consolidate skill (Sweller et al., 2011; Sweller et al., 2019), and the descriptive tendency observed here is consistent with such accounts and warrants future confirmatory investigation with larger samples.

Table 3. Comparison of EDA Averages Among Groups

Group	n	Avg.	SD	Min	Max	H	p
Novice	10	7.13	4.00	1.62	15.65		
Competent	9*	10.57	6.90	5.10	26.38	1.621	0.445
Expert	10	7.89	5.12	3.25	18.69		

Note. Values are in µS. One participant in the competent group was excluded from the GSR analysis due to a negative value (-11.92 µS) attributable to EDA baseline drift, which fell outside physiologically plausible limits.

Descriptively, within-group variability in GSR values was broadly comparable across groups, with slightly wider dispersion observed in the competent group (range 5.10-26.38 µS) than in the novice (range 1.62-15.65 µS) or expert (range 3.25-18.69 µS) groups. No systematic pattern of between-group variability emerged from the current data.

Between-group differences in the normalised SCR count (per minute) were also not statistically significant ($H = 0.403$, $p = 0.818$, $\eta^2 = -0.059$; see Table 4). Novice players showed a mean rate of 11.69 SCRs/minute (SD = 3.54), competent players 10.17 SCRs/minute (SD = 5.11), and expert players 11.23 SCRs/minute (SD = 3.38).

Table 3. Comparison of EDA Averages Among Groups

Group	n	Avg.	SD	Median	H	p
Novice	10	11.69	3.54	11.39		
Competent	10	10.17	5.11	10.99	0.403	0.818
Expert	10	11.23	3.38	10.78		

Note. Raw SCR counts were normalised per minute by dividing by individual recording duration (SCR count ÷ recording duration × 60).

The number of event-related SCRs (ER-SCRs) observed was low across all groups: two in the novice group (P7 = 0.75 µS; P9 = 0.03 µS), three in the competent group (P3 = 0.29 µS; P12 = 0.11 µS; P22 = 0.10 µS), and none in the expert group. Given the low observed counts and the absence of ER-SCRs in one of the three groups, an inferential comparison was not conducted; these observations are reported to support case-level descriptions rather than as group-level effects.

5. Discussion

This study examined the visual attention distributions and physiological responses of Valorant players across three groups- novice, competent, and expert- using a cross-sectional, quasi-experimental, between-groups laboratory design integrated within the PDH framework. The primary methodological contribution of the study lies in the integrated application of eye-tracking, EDA, WoZ, and pre- and post-test procedures for the joint interpretation of quantitative psychophysiological and qualitative data, alongside an AOI-normalisation procedure that jointly controls for AOI size disparity and session-length variability. Because none of the between-group comparisons on the eye-tracking or EDA measures reached statistical significance, the discussion is framed around descriptive patterns and effect-size estimates, both intended to inform the design of subsequent psychophysiological research procedures rather than to establish confirmatory group-level effects.

5.1. Visual Attention Distributions

Across all three groups, the game area and map AOIs received the largest share of visual attention, consistent with the tactical demands of Valorant's first-person shooter format. Descriptively, novice players allocated a higher proportion of their fixations to the game area than competent or expert players, whereas expert players showed the highest descriptive proportion on the map AOI. One possible interpretation- to be tested in larger and adequately powered samples- is that visual attention may become progressively distributed across peripheral tactical AOIs as competitive rank increases, with less concentration on the central gameplay viewport. However, given the non-significant Kruskal-Wallis results and the small effect sizes observed here, this interpretation cannot be supported by inferential evidence from the present data.

The descriptive tendency for competent players to allocate a slightly higher share of fixations to the team information AOI, and for novice players to show a numerically higher share of fixations on the ability bar, could be tentatively linked to accounts of skill acquisition in which intermediate-level performers actively negotiate team-based information while less experienced players still monitor core interface elements to support basic game mechanics (Luo et al., 2025). Because these patterns did not reach significance, these theoretical connections should be regarded as candidate patterns worthy of confirmatory testing rather than as confirmed relationships.

5.2. Physiological Responses

Mean skin conductance (GSR) values were descriptively highest in the competent group and lower and broadly comparable in the novice and expert groups, but this pattern did not reach statistical significance. Prior theoretical accounts have proposed that intermediate-level performers may experience elevated cognitive load as they consolidate skill without yet having reached automaticity (Sweller et al., 2011; 2019). The present descriptive tendency is broadly consistent with this account and may motivate confirmatory testing with adequately powered samples; however, it cannot be interpreted as evidence of

cognitive load differences between groups, given the non-significant result and the small observed effect size.

Normalised SCR counts per minute did not differ significantly between groups. Event-related SCRs were observed in only five participants across the two lower-skill groups and in none of the expert players; these counts were too small to support inferential comparisons and are reported only to support case-level observations. No conclusions regarding physiological regulation or automaticity can be drawn from the absence of ER-SCRs in the expert group.

5.3. Self-reported Preparation, Training, and Decision-Making

Pre- and post-test responses revealed descriptive variation across expertise groups in reported pre-game preparation routines, training habits, and decision-making styles. Because inferential testing was not conducted for these categorical responses, the observed proportions should be interpreted as descriptive patterns rather than as evidence of between-group differences. Notably, a higher proportion of expert players reported an intuitive decision-making style, whereas competent and novice players more frequently reported a tactical/analytical approach; this pattern is descriptively consistent with theoretical accounts of skilled performance, in which extensive practice may enable increasingly rapid, experience-based decisions (Ericsson & Kintsch, 1995), although it cannot serve as confirmatory evidence for such accounts within the present data. Notably, Table 1 shows that expert players in the present sample reported the shortest Valorant experience but the highest average weekly playing time. Rather than reflecting the cumulative duration of exposure, competitive rank in this sample was more closely associated with practice intensity- a pattern consistent with theoretical accounts emphasising the role of deliberate practice in skill acquisition (Ericsson & Kintsch, 1995).

5.4. Methodological Contribution

Independent of the specific inferential outcomes, the present study illustrates the systematic application of the PDH technique in an esports context, integrating pre- and post-test responses with concurrent eye-tracking and EDA measurement. The AOI-level normalisation procedure applied here- expressing fixation duration as a proportion of total recording time- controls simultaneously for AOI size disparity and session-length variability, and may be useful in future eye-tracking studies of dynamic game interfaces where these two confounds typically co-occur. Together with the reported effect-size estimates, the descriptive patterns identified in this sample may serve as reference values for the sample-size planning of subsequent confirmatory studies.

6. Conclusion

This study applied the Psychophysiological Data Harvesting (PDH) technique within a cross-sectional, quasi-experimental, between-groups laboratory design to examine visual attention distributions and physiological responses in Valorant players across three self-reported skill levels (novice, competent, expert; n = 10 per group). The primary aim of the study was not to establish confirmatory evidence of expertise-related differences, but to demonstrate the systematic application of an integrated psychophysiological data-collection procedure that combines quantitative and qualitative measures, and to generate descriptive patterns and effect-size estimates that may guide the design of subsequent confirmatory research. Descriptive tendencies were observed across the eye-tracking and EDA measures, but none of the between-group comparisons were statistically significant.

The main methodological contribution of the study lies in the integrated use of pre- and post-test data, eye-tracking, and EDA within the PDH framework, together with an AOI-normalisation procedure that jointly controls for AOI size disparity and session-length variability. The descriptive patterns and effect-size estimates reported here may serve as reference values for sample-size planning in confirmatory studies with larger and more diverse samples.

7. Limitations

Several limitations should be acknowledged. First, the sample size (n = 10 per group; N = 30) is small, and the statistical power of the between-group comparisons is therefore limited. Although this sample size falls within the range commonly reported in laboratory-based eye-tracking and psychophysiological research (Holmqvist et al., 2011; Cowley et al., 2014b), it does not permit the detection of small effects. The effect sizes reported alongside the Kruskal-Wallis tests are intended to support sample-size planning in subsequent research procedures rather than to substitute for such planning. Generalisation beyond this specific sample requires larger and adequately powered follow-up studies, including studies with participants from different cultural contexts.

Second, although the controlled laboratory environment enhanced measurement precision and internal validity, it also removed participants from their natural gaming context. As Holmqvist and colleagues (2011) emphasise, laboratory conditions in eye-tracking research improve data quality, but the requi-

rement to remain in a fixed position may create an interaction environment that differs from everyday gameplay.

Third, due to the physiological nature of EDA measurement, stimulus-locked phasic responses were observed only in a subset of participants. Given the low ER-SCR counts and the absence of responses in one of the three groups, these data were not used for inferential comparisons and were instead reported to support case-level observations.

Fourth, while eye-tracking data indicate where and for how long visual attention is directed, they do not in themselves reveal the underlying cognitive processes. The qualitative pre- and post-test responses used to contextualise the eye-tracking findings rely on participants' retrospective recall and may therefore be subject to recall bias and social desirability effects.

Fifth, although the WoZ contributed to the standardisation of game scenarios, it may not fully reflect the unstructured competitive dynamics of natural online play.

Sixth, gender was not balanced across expertise groups (see Table 1); female participants were more heavily represented in the expert group and less represented in the novice group. Because the study was not designed to examine gender-related differences, gender was not entered as a covariate in the analyses; however, this imbalance should be considered when interpreting the descriptive patterns.

Seventh, peak competitive rank and self-reported FPS gaming experience beyond Valorant were not collected as structured survey items in the pre-test questionnaire; future studies should collect these variables systematically to enable more detailed characterisation of expertise-related differences.

8. Recommendations For Future Research

Future confirmatory research should extend the present findings with larger and adequately powered samples, including players from different cultural contexts and, where feasible, professional-level players. Longer recording sessions and repeated-measures designs would allow the temporal dynamics of expertise-related attentional and physiological patterns to be examined in greater depth. The descriptive patterns observed here- the higher proportional attention allocated to the game area by novice players, the higher descriptive share on the map AOI in expert players, and the elevated GSR mean in competent players- represent candidate patterns that warrant confirmatory testing in subsequent studies.

From a practical perspective, the AOI-normalisation procedure applied here may be adopted by future eye-tracking studies of dynamic game interfaces in which AOI size disparity and session-length variability co-occur. The integrated PDH design, combining self-report, eye-tracking, and EDA data, may also be useful in future esports research as a framework for characterising player experience across multiple layers. Together, these methodological elements- the integrated PDH procedure and the AOI-normalisation approach- may support the design of subsequent psychophysiological research procedures in esports and game studies more broadly.

Funding

This study was supported under the Scientific Research Project titled "Expanding the Esports Ecosystem: Enhancing the Player Experience through Psychophysiological Data Harvesting" (IF-22001) at Aydın Adnan Menderes University.

Acknowledgement

We are grateful for the support of the AMT-LAB researchers, Arda Taşer, Nursinem Ülger, Ömer Tuna, Zeynep Sude Türkkol, and Begim Zholdubai Kyzy, who, acting as the "Wizard of Oz" team, managed the flow of the game with the participants from behind the scenes. We also extend our thanks to all participants who took the time to take part in the study, as well as to the project team.

Ethics Committee Approval

Ethics committee approval was received for this study from the ethics committee of Aydın Adnan Menderes University (Date: Oct 13, 2022, Decision Number: 31906847/050.04.04-08-177).

Competing Interests

The authors declare no competing interests.

References

Aisyah, I. H. (2023). Analysis of animated films in the Valorant game: A systematic literature review. Journal of Applied Multimedia and Networking, 7(2), 13-19.

https://doi.org/10.30871/jamn.v7i2.6806

Aydın, S., Depboylu, K., & Erdem, N. (2021). Biometric data harvesting: Proposals on remote biometric data harvesting and measurements in human behaviour scope. Current Debates on Social Sciences: Human Studies (s. 107-113). In Bilgin Kültür Sanat Yayınları.

Bányai, F., Griffiths, M. D., Király, O., & Demetrovics, Z. (2019). The psychology of esports: A systematic literature review. Journal of Gambling Studies, 35(2), 351-365. https://doi.org/10.1007/s10899-018-9763-1

Boucsein, W. (2012). Electrodermal activity (2nd ed.). Springer. https://doi.org/10.1007/978-1-4614-1126-0

Cheng, M., Chen, L., Pan, Q., Gao, Y., & Li, J. (2023). E-sports playing and its relation to lifestyle behaviors and psychological well-being: A large-scale study of collegiate e-sports players in

China. Complementary Therapies in Clinical Practice, 51, Article 101731. https://doi.org/10.1016/j.ctcp.2023.101731

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates. https://utstat.toronto.edu/~brunner/oldclass/378f16/readings/CohenPower.pdf

Cowley, B., Charles, D., Black, M., & Hickey, R. (2013). Real-time rule-based classification of player types in computer games. User Modeling and User-Adapted Interaction, 23, 489-526. https://doi.org/10.1007/s11257-012-9126-z

Cowley, B., Fantato, M., Jennett, C., Ruskov, M., & Ravaja, N. (2014a). Learning when serious: Psychophysiological evaluation of a technology-enhanced learning game. Educational Technology & Society, 17(1), 3-16. http://www.jstor.org/stable/jeductechsoci.17.1.3

Cowley, B., Kosunen, I., Lankoski, P., Kivikangas, J. M., Järvelä, S., Ekman, I., Kemppainen, J., & Ravaja, N. (2014b). Experience assessment and design in the analysis of gameplay. Simulation & Gaming, 45(1), 41-69. https://doi.org/10.1177/1046878113513936

Dahlbäck, N., Jönsson, A., & Ahrenberg, L. (1993). Wizard of Oz studies- why and how. Knowledge-Based Systems, 6(4), 258-266. https://doi.org/10.1016/0950-7051(93)90017-N

Denisova, A., & Cairns, P. (2015). Adaptation in digital games: The effect of challenge adjustment on player performance and experience. In Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play (pp. 97-101). Association for Computing Machinery. https://doi.org/10.1145/2793107.2793141

Diass, E. C., Jonemaro, E. M. A., & Afirianto, T. (2022). Evaluasi user experience gim Valorant menggunakan metode enhanced cognitive walkthrough pada pengguna baru. Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer, 6(7), 3422-3431. https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/11367/5030

Drachen, A., Nacke, L. E., Yannakakis, G. N., & Pedersen, A. L. (2010). Correlation between heart rate, electrodermal activity, and player experience in first-person shooter games. In Proceedings of the 5th ACM SIGGRAPH Symposium on Video Games (pp. 49-54). Association for Computing Machinery. https://doi.org/10.1145/1836135.1836143

Dreyfus, S. E., & Dreyfus, H. L. (1980). A five-stage model of the mental activities involved in directed skill acquisition (Operations Research Center Report No. 80-2). University of California, Berkeley. https://www.semanticscholar.org/paper/A-Five-Stage-Model-of-the-Mental-Activities-in-Dreyfus-Dreyfus/efa296060526e40fb81b7498786aba72d546e555

Ericsson, K. A., & Kintsch, W. (1995). Long-term working memory. Psychological Review, 102(2), 211-245. https://doi.org/10.1037/0033-295X.102.2.211

Gaming in Turkey. (2020). Türkiye game market 2020 report. https://www.gaminginturkey.com/turkiye-oyun-sektoru-raporu-2020.pdf

Hamari, J., & Keronen, L. (2017). Why do people play games? A meta-analysis. International Journal of Information Management, 37(3), 125-141. https://doi.org/10.1016/j.ijinfomgt.2017.01.006

Hedlund, D. P. (2023). A typology of esports players. Journal of Global Sport Management, 8(2), 460-477. https://doi.org/10.1080/24704067.2021.1871858

Himmelstein, D., Liu, Y., & Shapiro, J. L. (2017). An exploration of mental skills among competitive League of Legends players. International Journal of Gaming and Computer-Mediated Simulations, 9(2), 1-21. https://doi.org/10.4018/IJGCMS.2017040101

Hindin, J., Hawzen, M., Xue, H., Pu, H., & Newman, J. (2020). E-sports. In Routledge Handbook of Global Sport (pp. 405-415). Routledge. https://doi.org/10.4324/9781315714264

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & Van de Weijer, J. (2011). Eye tracking: A comprehensive guide to methods and measures. Oxford University Press.

İcil Tuncer, A., Aytekin, B. A., Aydın, M. S., Erdem, N., Depboylu, K., Ulusoy, T. A., Üveyik, B., Kızılhan, T. (2023). Evaluating the relationship between logo and corporate reputation with psychophysiological data harvesting technique. Business & Management Studies: An International Journal, 11(2), 413-434. https://doi.org/10.15295/bmij.v11i2.2180

Kamal, R., & Saeed, H. (2025). The future of AI in e-sports and competitive gaming. Frontiers Social Sciences Research Review, 1(2), 27-33. https://journalofsocialscience.com/index.php/Journal/article/view/50

Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. Journal of the American Statistical Association, 47(260), 583–621. https://doi.org/10.1080/01621459.1952.10483441

Luo, Y., Chen, Y., Cho, J., Yan, C., & Seo, J. (2025). Differences in eye movement characteristics between expert and non-expert esports players: A systematic review and meta-analysis. Scientific Reports, 15, 30185, https://doi.org/10.1038/s41598-025-12101-8

Mangat, H. S., Urbán, R., Koncz, P., Demetrovics, Z., Czakó, A., Griffiths, M. D., & Király, O. (2025). Personality, motivations, and gaming disorder symptoms: A large-scale comparative study of esports players, highly engaged gamers, and recreational players. Comprehensive Psychiatry, 142, 152623, https://doi.org/10.1016/j.comppsych.2025.152623.

Martins, D. J. D. Q., Moraes, L. C. L., & Marchi Júnior, W. (2022). COVID-19 impacts on school sports events: An alternative through E-sports. Managing Sport and Leisure, 27(1-2), 45-49. https://doi.org/10.1080/23750472.2021.1928537

Nacke, L. E. (2015). Games user research and physiological game evaluation. In R. Bernhaupt (Ed.), Game user experience evaluation (pp. 63-86). Springer. https://doi.org/10.1007/978-3-319-15985-0_4

Pernice, K., & Nielsen, J. (2009). How to conduct eyetracking studies. Nielsen Norman Group. https://www.nngroup.com/reports/how-to-conduct-eyetracking-studies/

Rahmawati, D., Mulyana, D., & Safitri, D. (2019). Knowledge sharing dynamics among Dota 2 Online gamers at Indonesian internet cafes. SEARCH (Malaysia), 11(3), 41-53. https://fslmjournals.taylors.edu.my/wp-content/uploads/SEARCH/SEARCH-2019-11-3/SEARCH-2019-P3-11-3.pdf

Riedl, E., & Verschuuren, P. (2025). A systematic literature review of esports integrity. The International Sports Law Journal, 25, 99-118. https://doi.org/10.1007/s40318-025-00295-y

Rienzo, A., & Cubillos, C. (2020). Playability and player experience in digital games for the elderly: A systematic literature review. Sensors, 20(14), 3958. https://doi.org/10.3390/s20143958

Riot Games. (2026). Valorant competitive mode FAQ. https://support.riotgames.com/en-us/valorant/gameplay/valorant-competitive-mode-faq

Salvucci, D. D., & Goldberg, J. H. (2000). Identifying fixations and saccades in eye-tracking protocols. In Proceedings of the 2000 Symposium on Eye Tracking Research & Applications (pp. 71-78). https://doi.org/10.1145/355017.355028

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). Experimental and quasi-experimental designs for generalized causal inference. Houghton Mifflin.

Statista. (2025). Global esports audience size from 2019 to 2025, by viewer type. https://www.statista.com/statistics/490480/global-esports-audience-size-viewer-type/?srsltid=AU7gw4UXRsfnx5vbv3pFrgSbqcAFcjR6_zTnQSy3ZlutgxyLzw9bvBl1

Sweller, J., Ayres, P., & Kalyuga, S. (2011). Cognitive load theory. Springer. https://link.springer.com/book/10.1007/978-1-4419-8126-4

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. Educational Psychology Review, 31(2), 261-292. https://doi.org/10.1007/s10648-019-09465-5

Tammi, T., Pekkanen, J., Cowley, B. U., & Lappi, O. (2025). Quantifying tracking quality during occlusion with an integrated gaze metric anchored to task performance. Scientific Reports, 15, 31858. https://doi.org/10.1038/s41598-025-17519-8

Thiel, A., & John, J. M. (2018). Is eSport a 'real' sport? Reflections

on the spread of virtual competitions. European Journal for Sport and Society, 15(4), 311-315. https://doi.org/10.1080/16138171.2018.1559019

Vasiljevic, G., & Miranda, L. (2020). A general model for electroencephalography-controlled brain-computer interface games. In O. Gervasi et al. (Eds.), Computational science and its applications-ICCSA 2020 (pp. 174-189). Springer. https://doi.org/10.1007/978-3-030-58802-1_13

Wang, C. C., Chen, H. C., & Hung, J. C. (2022). Employing portable eye tracking technology in the visual attention of cognitive process: A case study of digital game-based learning. In International Conference on Innovative Technologies and Learning (pp. 480-490). Springer. https://doi.org/10.1007/978-3-031-15273-3_53

Webster, A. (2020, March 30). Riot's shooter Valorant goes into beta on April 7th. The Verge. https://www.theverge.com/2020/3/30/21199452/valorant-multiplayer-shooter-riot-closed-beta-date

Wiemeyer, J., Nacke, L. E., Moser, C., & Mueller, F. F. (2016). Player experience. In R. Dörner, S. Göbel, W. Effelsberg, & J. Wiemeyer (Eds.), Serious games: Foundations, concepts and practice (pp. 243-271). Springer. https://doi.org/10.1007/978-3-319-40612-1_9

Yang, L., Zhang, W., Li, P., Tang, H., Chen, S., & Jin, X. (2025). The aiming advantages in experienced first-person shooter gamers: Evidence from eye movement patterns. Computers in Human Behavior, 165, 108573. https://doi.org/10.1016/j.chb.2025.108573