Chapter 8. ARTIFICIAL INTELLIGENCE IN ESPORTS AS A CASE OF DIGITAL TRANSFORMATION IN PHYSICAL CULTURE EDUCATION

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***Abstract**. This chapter aims to systematize and analyze scientific publications on the use of artificial intelligence and machine learning in esports to identify major research trends and development directions, and to interpret this field as a case of digital transformation in physical culture education under conditions of social uncertainty. Based on a focused selection process, 81 scientific papers indexed in the Web of Science Core Collection from 2008 to the first quarter of 2026 were analyzed. The review identifies eight major thematic areas that reflect the current integration of intelligent technologies into the esports ecosystem: match outcome prediction, player-performance and behavior analysis, AI agents and game automation, physiology, health and emotional-state monitoring, spectator experience and media support, social interaction and communication, business and economic applications, and dataset development. The findings show that AI in esports extends beyond isolated technical solutions and reveals a technologically dense professional environment shaped by predictive systems, biometric monitoring, data-driven decision-making, and algorithmically mediated evaluation. In this perspective, esports is considered not only as a distinct competitive domain but also as a concentrated analytical case that helps clarify broader changes relevant to physical culture education. The chapter argues that the identified tendencies point to the growing importance of data literacy, AI literacy, ethical awareness, adaptive judgment, and professional resilience in the preparation of future specialists. The results contribute to both the systematization of research on AI in esports and the broader discussion of leadership and educational adaptation in digitally transformed environments.*

***Keywords**: esports; artificial intelligence; machine learning; systematic review; digital transformation.*

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Introduction

The digital transformation of education increasingly extends beyond the adoption of isolated technologies and is now associated with deeper changes in professional preparation, decision-making models, assessment practices, and the distribution of expertise between humans and intelligent systems. This shift is especially visible in domains where professional performance depends on rapid data interpretation, continuous adaptation, and technologically mediated action. In such fields, education is compelled to respond not only to innovation itself but also to social uncertainty, that is, to unstable skill demands, accelerated obsolescence of tools, and the growing need to prepare learners for roles that are being reconfigured by artificial intelligence. International policy and research literature increasingly frames AI not as a narrow technical add-on but as a force that may alter how education systems define competencies, support decision-making, and prepare individuals for work in evolving environments (OECD, 2024; OECD, 2026; UNESCO, 2023).

Within this broader transformation, physical culture education deserves particular attention. It is no longer limited to training in motor skills, coaching methods, or performance management in their conventional forms. The expansion of AI-based monitoring, predictive modeling, biometric assessment, video analytics, and adaptive feedback systems is changing how performance is measured, interpreted, and improved in sport-related settings. Recent scholarship shows that AI is already reshaping sports education and training through individualized learning paths, real-time feedback, data-driven evaluation, and more personalized instructional adjustment. At the same time, this shift generates new educational demands: future professionals must be able to interpret algorithmic outputs, work with digital performance data, understand the limits of automated recommendations, and make responsible decisions in environments where technological systems increasingly influence training and assessment (Gao et al., 2025).

Esports provides a particularly revealing case for analyzing these changes. Although it emerged outside traditional educational structures, it has evolved into a technologically saturated professional field in which AI is used for outcome prediction, player-performance analysis, behavioral profiling, physiological monitoring, automated decision support, media production, and strategic modeling. Because esports operates under conditions of rapid patch cycles, unstable meta-configurations, and constant platform-level change, it offers a concentrated example of what professional activity looks like when knowledge becomes quickly outdated and when human expertise is increasingly intertwined with algorithmic systems. In that sense, esports can be interpreted not only as a specialized competitive domain but also as an analytical lens through which broader transformations in physical culture education become more visible. The review-based mapping of AI applications in esports, therefore, has value beyond the industry itself: it helps identify the types of competencies, vulnerabilities, and leadership responses that may become increasingly relevant across digitally transformed sport and education environments.

This perspective also foregrounds the issue of resilience. In this chapter, resilience is understood not merely as psychological endurance but as a professional and educational capacity to maintain meaningful action in conditions of technological volatility, informational overload, ethical ambiguity, and shifting performance criteria. Such a view is important because the integration of AI into sport-related practice creates not only new opportunities but also new tensions concerning privacy, explainability, bias, accountability, and the governance of biometric and behavioral data. A recent scoping review on the ethical implications of AI in sport shows that privacy and data ethics, fairness and bias, transparency, and accountability are now among the most persistent concerns in this area. This means that educational leadership in physical culture and sport can no longer focus exclusively on performance enhancement. It must also address the conditions under which digital tools are adopted, interpreted, and regulated, as well as how future professionals are prepared to act responsibly in the face of uncertainty (Kim et al., 2025; OECD, 2024; UNESCO, 2023).

Against this background, the analysis of scientific publications on artificial intelligence in esports can be treated as a case within a broader case: on the one hand, it systematizes a rapidly growing research field; on the other, it opens a pathway for interpreting esports as a high-intensity manifestation of digital transformation in physical culture education. Such a reading allows the review to preserve its analytical integrity while extending its significance to questions of educational adaptation, interdisciplinary training, professional resilience, and leadership under conditions of social uncertainty.

Research Questions:

RQ1. What major directions of artificial intelligence application in esports are represented in contemporary scientific literature, and how are these directions distributed across the current research field?

RQ2. How can the case of AI integration in esports be interpreted as an indicator of digital transformation in physical culture education and as a basis for rethinking leadership, professional resilience, and educational adaptation under conditions of social uncertainty?

Research Results

AI in esports: analysis of current research and development prospects

The literature search was conducted in the Web of Science Core Collection (WoS CC) bibliometric database for the period from 2008 to the first quarter of 2026. The decision to use WoS CC as the sole database was based on several considerations: 1) WoS CC maintains rigorous quality standards through selective indexing of high-impact journals, ensuring the inclusion of peer-reviewed, high-quality research; 2) it provides comprehensive coverage across multiple disciplines relevant to this study, including computer science, sports science, and human-computer interaction; 3) its citation indexing capabilities enable advanced bibliometric analysis; 4) preliminary searches in other databases (Scopus, PubMED) revealed substantial overlap in core publications, with WoS CC capturing the majority of seminal works in this emerging field.

The following search query was applied:

(("artificial intelligence" OR "machine learning" OR "AI") AND (esports OR "e-sports" OR "electronic sports")).

The screening process followed a systematic two-stage approach:

Stage 1. Initial screening (n=121). All 121 articles retrieved from the initial search underwent title and abstract screening by two independent reviewers. At this stage, articles were assessed for their relevance to AI/ML applications in esports using the inclusion/exclusion criteria (Table 1). Disagreements between reviewers were resolved through discussion and, when necessary, consultation with a third reviewer.

Table 1
Inclusion and Exclusion Criteria

Inclusion criteria:	*Exclusion criteria:*
• Peer-reviewed journal articles and conference proceedings indexed in WoS CC • Publications explicitly addressing AI or machine learning applications in esports contexts • Studies focusing on competitive gaming environments (professional, semi-professional, or amateur esports) • Empirical research, systematic reviews, technical implementations, or theoretical frameworks • Publications in English • Time frame: January 2008 to March 2026	• Non-peer-reviewed materials (editorials, opinion pieces, news articles) • Studies addressing recreational gaming without a competitive esports context • Publications focused solely on game development or design without AI/ML components • Duplicate publications (same study published in multiple venues) • Studies where AI/esports appeared only tangentially in keywords without substantive discussion • Non-English publications (due to resource constraints for accurate translation and interpretation)

Source: developed by the authors based on the inclusion and exclusion criteria applied in the WoS Core Collection search strategy.

Stage 2. Full-text assessment (n=81). Articles passing the initial screening underwent full-text review to confirm eligibility.

Duplicate detection was performed through both automated and manual methods:

1. WoS built-in duplicate detection algorithms identified initial duplicates
2. Manual verification through cross-referencing DOIs, author lists, and publication dates
3. When multiple publications reported the same study (e.g., conference paper and subsequent journal article), the most comprehensive version was retained, typically favoring journal publications over conference proceedings due to extended peer review and methodological detail

No duplicate publications were identified in the final dataset, as WoS CC's indexing protocols effectively prevent duplicate entries for the same work.

The quality of each publication was assessed on the following dimensions:

For empirical studies: methodological rigor (sample size adequacy, appropriate statistical methods); clarity of research design and reproducibility; transparency in data collection and analysis procedures; acknowledgment of limitations;

For technical/computational studies: clarity of ai/ml methodology and implementation details; benchmark comparisons or validation procedures; reproducibility (code availability, dataset accessibility); discussion of generalizability and limitations;

For review articles: systematic search methodology; transparency in inclusion/exclusion criteria; synthesis approach and theoretical framework.

Based on the search results, a co-occurrence network map was created to visualize the thematic structure of the field using VOSviewer 1.6.18 (VOSviewer version 1.6.18, 2021), a software tool for constructing and visualizing bibliometric networks (Fig. 1). The analysis employed keyword co-occurrence and direct citation analysis methods to identify conceptual clusters within the literature.

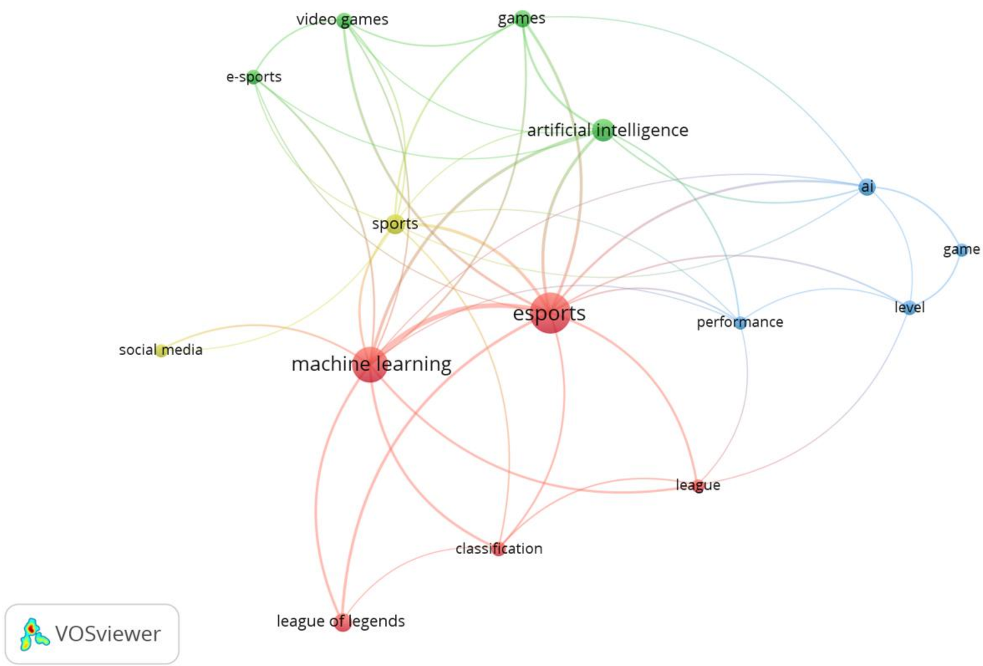

Figure 1

Areas of application of artificial intelligence technologies in esports (analysis of related words, visualization of cluster density, weight – citations)

Source: own research based on data obtained from Web of Science Core Collection and analyzed using VOSviewer (02.02.2026).

The network is built on the basis of 15 elements – keywords. The size of the keywords corresponds to the number of references obtained, and the spatial proximity reflects the strength of the relationship between the subjects. They are grouped into 4 clusters:

Cluster 1 (5 items): classification, esports, league, league of legends, machine learning;

Cluster 2 (4 items): artificial intelligence, e-sports, games, video games;

Cluster 3 (4 items): ai, game, level, performance;

Cluster 4 (2 items): social media, sports.

Analysis of publications by category showed that the largest number of works are represented in the following categories: Computer Science – Artificial Intelligence (40), Software

Engineering (34), Information Systems (27), Interdisciplinary Applications (24), Theory & Methods (24), Cybernetics (13); Engineering – Electrical & Electronic (18); Telecommunications (12).

The provided bar chart illustrates the temporal progression of scholarly interest in the application of artificial intelligence within the esports domain from 2008 to the first quarter of 2026 (Fig. 2).

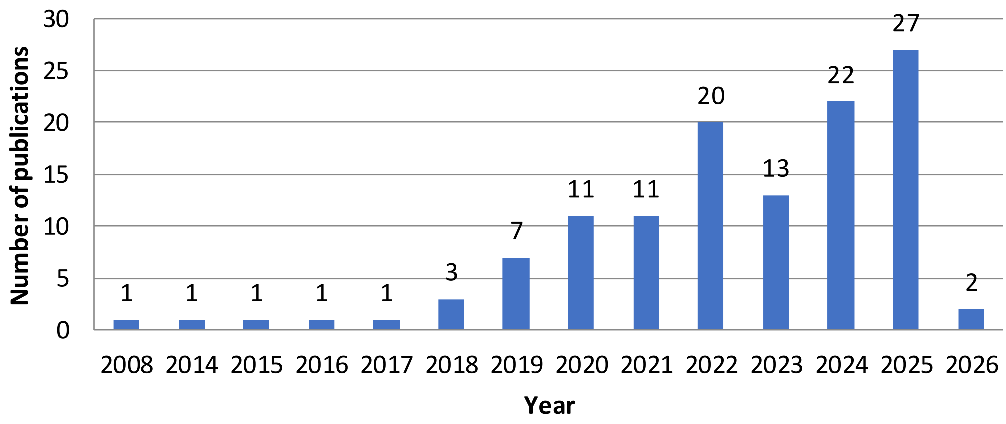

Figure 2
Dynamics of publications by year

Source: Authors' own work.

The data reveal a distinct shift from a nascent field to a rapidly accelerating area of interdisciplinary research. Between 2008 and 2018, only 6.61% of the total number of articles were published. The highest percentage of articles, accounting for 67.77%, was published during the period from 2022 to 2025. This trajectory underscores a growing institutional recognition of esports as a complex object of scientific analysis, requiring sophisticated AI tools for performance optimization, strategic forecasting, and spectator engagement.

Based on the reviewed literature, scientific articles can be classified according to the following thematic areas, which reflect various aspects of the application of artificial intelligence (AI) in esports:

1. Predicting match results (Win Prediction).

2. Analysis of player performance and behavior.

3. AI agents and game process automation.

4. Physiology, health, and emotional state.

5. Viewing experience, broadcasts, and media.

6. Social aspects, communication, and NLP (Natural Language Processing).

7. Business, marketing, and economics.

8. Creating datasets.

This review acknowledges several limitations: 1) While WoS CC provides comprehensive coverage, relevant publications in other databases may have been missed; 2) English-only inclusion may exclude relevant research in other languages; 3) Emphasis on peer-reviewed publications may exclude gray literature, technical reports, or industry white papers; 4) The rapidly evolving nature of both AI technology and esports means recent developments may not yet appear in indexed literature; 5) The heterogeneity of study designs necessitated a flexible rather than standardized quality appraisal approach.

1. Predicting match results (win prediction). Win prediction constitutes the most extensively developed thematic cluster in the reviewed literature, encompassing studies across multiplayer online battle arena (MOBA), first-person shooter (FPS), and mobile game genres. Three cross-cutting findings characterize this body of work. First, ensemble learning methods – notably XGBoost and Random Forest – consistently outperform logistic regression and simpler classifiers across game genres (Chowdhury et al., 2025; Xia et al., 2025; Birant & Birant, 2023; Birant, 2022). Second, models integrating pre-match draft data with real-time in-game statistics demonstrate superior predictive validity relative to those drawing on either data source in isolation (Chowdhury et al., 2025; Costa et al., 2021; Chen et al., 2020). Third, the subfield is undergoing a methodological reorientation – from black-box accuracy optimization toward interpretable modeling frameworks: the application of Shapley Additive exPlanations (SHAP) and explainable artificial intelligence (XAI) methods enables identification of the specific game-state features –

including gold income, damage output, and champion synergy – that drive predicted outcomes (Galán-Sales et al., 2024; Jing et al., 2025; Yang et al., 2022).

Within the draft-phase subgroup, the available evidence confirms that hero or champion selection constitutes a substantive predictive signal independent of in-game performance. Historical performance records have been identified as the most reliable pre-match feature (Costa et al., 2021), whereas models that incorporate player-specific skill ratings and inter-champion synergy indices yield further improvements in predictive accuracy (Hitar-García et al., 2023). Graph-based approaches that model league-wide team relationships over a full competitive season have achieved state-of-the-art performance (Bisberg & Ferrara, 2022), and role-weighted metrics have improved upon aggregate team statistics by accounting for positional responsibilities (Bahrololloomi et al., 2022; Yoon & Jeong, 2025).

Real-time and in-game prediction represents a substantively distinct and practically significant research direction. Models trained on the initial five to ten minutes of match data achieve predictive accuracy of 74–85%, facilitating early strategic assessment for players and analysts (Hodge et al., 2021; Wilathgamuwa, 2024). Spatio-temporal architectures developed for the mobile MOBA title Honor of Kings extend this capability by generating interpretable, timestep-level predictions that decompose the contribution of individual game events to the evolving match outcome (Yang et al., 2022; Tian et al., 2022). A methodologically notable extension involves predicting comeback victories rather than outright match winners, employing bounty-based mechanics to model the conditions under which a losing team can reverse a late-game deficit (Lee & Kim, 2025; Kamal et al., 2026).

Despite the breadth of this subfield, a fundamental limitation persists: the predominant research design involves training and evaluating models on fixed historical datasets, leaving the reliability of deployed systems across game patches and evolving competitive meta-games largely unexamined. Cross-title generalization likewise remains rare – the concentration of studies on League of Legends and Dota 2 raises questions regarding the transferability of findings to games with structurally distinct mechanics.

2. Analysis of player performance and behavior. Research in this domain extends beyond match-level outcomes to examine how individual players act, make decisions, and perform within competitive game environments. Three methodological directions structure the literature: the development of novel performance metrics and rating systems, the automated classification of player roles and behavioral profiles, and the use of peripheral input data – including keyboard activity, mouse dynamics, and physiological sensors – for player profiling.

The most substantive methodological contribution of the metrics subgroup is the transition from outcome-contingent statistics (kills, deaths, assists) toward context-sensitive evaluation frameworks. Rather than quantifying the frequency of player actions, these approaches assess whether each discrete action – conditioned on the instantaneous game state – increased the team's probability of winning. This evaluative logic underpins both the PandaSkill framework for League of Legends, which updates player ratings on the basis of performance scores rather than match outcomes (De Bois et al., 2025), and Maymin's (2021) contextual reframing of kills and deaths as events that either advance or retard the team's win probability at a given moment. The xKills model extends this principle to FPS environments by estimating the probability of a successful elimination for each engagement opportunity, conditioned on spatial context (Gordon et al., 2024). Across these contributions, SHAP-based explainability methods are employed to identify the most diagnostically informative indicators – including kills per round, round-opening success rate, and pistol round rating – thereby supporting data-driven coaching interventions (Jing et al., 2025).

The role classification subgroup addresses a distinct analytical challenge: whether AI systems can reliably infer a player's positional role or strategic archetype from observable in-game behavior. Evidence across multiple genres indicates that this is feasible. Logistic regression applied to replay file data classifies player roles in Dota 2 with stable accuracy (Eggert et al., 2015), while clustering methods applied to PlayerUnknown's Battlegrounds (PUBG) data distinguish four behavioral archetypes

– Hunter, Sniper, Traveler, and Camper – based on aggression and mobility scores (Sagong et al., 2025). In League of Legends, video-based gameplay analysis enables automated classification of cooperative versus aggressive play styles, providing a foundation for personalized coaching systems that do not require manual annotation (Kim et al., 2021).

The input-data subgroup demonstrates that the manner in which a player interacts with hardware constitutes a reliable and discriminative signal of competitive skill. Telemetry data from sim racing – encompassing vehicle speed, steering angle, and lateral acceleration – separates elite from novice drivers with 97% classification accuracy (Hojaji et al., 2024a, 2024b). Keystroke and mouse movement sequences reliably distinguish professional players from amateurs and casual participants, with control mechanics emerging as a stronger predictor of elite-level membership than general gaming experience (Lange et al., 2022). Multimodal fusion of physiological and interaction data – including heart rate, hand activity, cursor movements, and gaze position – classifies League of Legends skill level at 90% accuracy via symbolic transfer entropy, suggesting that the integration of multiple sensory channels captures dimensions of cognitive engagement inaccessible to game log analysis alone (Noroozi et al., 2025).

A limitation common to all three subgroups is dataset specificity: models are trained and validated within a single title, and the extent to which behavioral and input-based markers generalize across games with differing mechanical demands remains unclear. Cross-title validation studies capable of distinguishing genre-specific from domain-general indicators of player skill and decision quality would substantially advance the field.

3. AI agents and game automation. Research on AI agents in esports is organized around two distinct and, in certain respects, opposed research objectives: the development of systems capable of defeating human players at the highest competitive level, and the development of systems designed to collaborate with human players to enhance team performance and training outcomes. These objectives entail divergent design requirements, and the bodies of literature addressing them have evolved largely independently.

The superhuman agent subgroup encompasses some of the most technically ambitious work in the reviewed literature. Across multiple game genres, reinforcement learning systems have attained or exceeded elite human performance benchmarks: AlphaStar achieved Grandmaster rank in StarCraft II across all three playable races through multi-agent training within a self-play league (Vinyals et al., 2019); Gran Turismo Sophy defeated world-class sim racing competitors via model-free deep reinforcement learning incorporating a reward function that penalised violations of racing etiquette (Wurman et al., 2022); agents trained through curriculum self-play and Monte Carlo Tree Search defeated top professional teams under an unrestricted hero pool in Honor of Kings (Ye et al., 2020); and a memristive hardware implementation enabled millisecond-level strategic adaptation in Street Fighter (Go et al., 2023). The unifying characteristic across these systems is not a shared algorithm but a common training paradigm: performance improvement through progressive self-play against increasingly capable opponents, rather than behavioral cloning from human demonstrations. A parallel line of work extends this paradigm to multiplayer FPS environments, where agents trained via Proximal Policy Optimization acquire survival, coordination, and combat improvement capabilities without human expert supervision (Piergigli et al., 2019).

Game preparation and strategy automation constitute a more applied research direction. An automated deck construction system for Hearthstone employs a utility-based optimization framework that accounts for mana curve composition, card synergy, and community meta-game data to generate competitive decks from a player's available card pool (Stiegler et al., 2016). Sequential pattern mining applied to real-time strategy games identifies recurring action sequences and quantifies their relative contribution to match outcomes, yielding a methodology applicable to both agent design and professional replay analysis (Bosc et al., 2014). Although fewer in number and narrower in scope than the superhuman agent literature, these studies address a practically significant problem: reducing cognitive overhead associated with strategic preparation in competitive play.

The human-AI collaboration subgroup addresses a fundamentally different question – not whether AI systems can win, but whether humans and AI agents can operate effectively as integrated teammates. Experimental evidence indicates that the presence of anonymous AI teammates in MOBA environments reduces toxic social dynamics and supports problem-focused coping strategies, whereas social robots are more effective in facilitating emotional regulation (Wang et al., 2023). Interview-based studies with professional esports players identify cross-training – defined as mutual comprehension of each partner's roles and capabilities – as a prerequisite for effective human-AI team functioning, with expert players characterizing AI as a coach or adaptive collaborator rather than a surrogate team member (Lancaster et al., 2025a). Player skill level moderates these requirements: higher-skilled players require AI systems oriented toward socio-emotional attunement and role-based awareness, whereas novices benefit primarily from procedural guidance (Lancaster et al., 2025b). Analysis of professional players in EA FC similarly identifies joint learning and shared team identity as necessary conditions for stable human-autonomy collaboration (Nols et al., 2026). Across these studies, a consistent finding emerges: the technical capability of an AI agent is insufficient to guarantee effective collaboration – successful human-AI teaming additionally requires trust, operational transparency, and adaptive task allocation that contemporary systems only partially provide.

Auxiliary infrastructure for agent development includes a standardized bot competition framework for Dota 2 that enables external AI controllers to participate in 1-on-1 matches under controlled conditions (Font & Mahlmann, 2019), and a design framework that identifies four key challenges – team coordination, in-game decision-making, game state tracking, and performance monitoring – where AI assistants can most productively support player development (Kleinman et al., 2022). The application of esports-derived reinforcement learning methods to naval combat simulation, yielding a win rate of approximately 90% with heterogeneous agent configurations, further demonstrates the cross-domain transferability of these methodologies (Chen & Nie, 2022).

A structural gap persists throughout this domain: research on superhuman agent performance and human-AI collaboration proceeds largely in isolation, with limited attention to the question of whether agents optimized for competitive superiority can be adapted to fulfill collaborative roles – or whether the training objectives of competitive AI are fundamentally at odds with the transparency and predictability that effective human-AI teaming requires.

4. Physiology, health, and emotional state. Research in this domain treats the esports player's body and cognitive system as objects of empirical measurement, employing AI and machine learning methods to detect, classify, and predict physiological and psychological states during competitive activity. The literature is organized into three analytical levels: neurological and cognitive state monitoring, psychological state identification, and physical health assessment.

The neurological monitoring subgroup establishes that brain activity measured prior to and during gameplay carries a reliable predictive and classificatory signal. Electroencephalography (EEG) data collected immediately before match commencement enables outcome prediction at 80% accuracy via the LightGBM algorithm, with beta-band activity in the parietal cortex identified as the primary biomarker – an approach that retains predictive validity in conditions where statistical performance models fail, including matches with unexpected outcomes (Minami et al., 2024). EEG recordings acquired during active gameplay discriminate between professional and amateur players at an F1-score of 95% and classify fatigue state at 90% accuracy, confirming that neuroimaging interfaces are capable of monitoring player condition in real time rather than solely in retrospective analysis (Melentev et al., 2020). Collectively, these findings establish pre-game cognitive state as a meaningful performance variable – one that coaching and athlete management practices have yet to systematically integrate.

The psychological state subgroup examines mental conditions that directly impair or enhance competitive performance but are not observable from game log data. The identification of tilt – an affective dysregulation state that degrades decision quality – and flow – a state of complete attentional absorption – from multimodal physiological, cognitive, and behavioral data establishes a methodological pathway toward early warning systems capable of intervening before performance deterioration becomes apparent (Manikandan et al., 2025). Eye-tracking analysis reveals that expert players process visual scenes qualitatively differently from novices, exhibiting broader horizontal gaze distribution and shorter fixation durations, indicative of faster perceptual integration rather than accumulated experience alone (Jeong et al., 2024). Mental workload, operationalized as a composite of subjective self-report and objective measures of heart rate variability and electrodermal activity, can be classified with 82% accuracy using a support vector machine across a sample of 96 participants, linking objective physiological measurement to the subjective cognitive demands that players report experiencing (Al Fawwaz et al., 2024). Voice communication analysis introduces a team-level dimension: emotion classifiers applied to tournament audio achieve 92.7% accuracy and reveal a significant positive correlation between the affective intensity of intra-team communication and competitive outcomes, suggesting that affective coordination constitutes a measurable component of collective performance (Abramov et al., 2022).

Physical health research reorients the domain's focus from performance optimization toward player welfare. A large-scale cross-sectional study conducted among 1,025 Brazilian players identified a pain prevalence of 60%, with the spine and wrists most frequently affected; gender differences in pain reporting were also observed, as was a counterintuitive association between prior physical therapy and elevated pain during gameplay, most plausibly attributable to pre-existing injury rather than treatment failure (Viana et al., 2025). This study is distinguished from others in the domain by framing esports within an occupational health paradigm – a conceptual approach that remains underrepresented in the broader literature.

A methodologically innovative subgroup applies esports as an instrument for supporting healthy aging. Infrared thermography of facial skin temperature during gameplay classifies emotional arousal states in older adults with over 90% accuracy, providing a non-invasive assessment tool applicable to populations at risk of dementia (Kikuchi et al., 2025). A subsequent study employs CNN-LSTM analysis of changes in facial color saturation in the cheek region to classify emotional valence (positive vs. negative) during gameplay, extending continuous affective monitoring to settings without specialized equipment (Kikuchi et al., 2024). These studies are notable not only for their methodological originality but also for conceptually repositioning esports as a potential public health intervention for older adult populations, rather than exclusively as a competitive youth medium.

Two limitations apply across the domain. Sample sizes are consistently small – the majority of studies involve fewer than 100 participants – and study populations are predominantly young and male, constraining the generalisability of findings to broader demographic groups. Additionally, laboratory data collection conditions, however rigorously controlled, may not adequately replicate the physiological demands of high-stakes competitive play, in which performance pressure, audience effects, and prize incentives introduce confounding variables that experimental designs cannot fully accommodate.

5. Viewing experience, broadcasts, and media. Research in this domain investigates how artificial intelligence transforms the relationship between esports competition and its audiences – encompassing both the visualization and narration of game data for viewers and the progressive automation of broadcast production processes. The literature is organized around three interconnected directions: data-driven storytelling and visualization, the cognitive and communicative design of AI-generated information for live audiences, and the automation of broadcast production tasks.

The data storytelling subgroup addresses a challenge specific to esports spectatorship: the gap between how match events unfold on screen and the comprehension available to viewers without specialized game knowledge. The DAX system, implemented within the Weavr companion application for ESL One tournaments, demonstrates that providing real-time, personalized statistics increases viewer engagement and deepens understanding of the strategic complexity that conventional broadcasts leave unexplained (Kokkinakis et al., 2020). A methodologically significant extension of this principle involves reframing prediction output from the question of who will win to that of how a team can win: the Win Condition model generates caster-oriented narratives structured around the game states a team must achieve to secure victory, thereby rendering AI-based analytics directly functional for broadcast storytelling rather than merely for predictive display (Chitayat et al., 2024a). The visualization of the underlying machine learning models – as demonstrated through the live broadcast integration of the WARDS ward-placement prediction model for Dota 2 – indicates that complex AI outputs can be rendered accessible to general audiences without material loss of analytical depth, provided that visual design principles foreground communicative clarity (Chitayat et al., 2024b). These studies collectively establish that the primary challenge in this domain is not predictive precision but communicative translation: the transformation of model outputs into audience-interpretable narratives.

The cognitive design subgroup empirically investigates how live audiences receive and process AI-generated information during broadcasts, with findings that complicate the assumption that increased informational richness improves viewer experience. Although viewers demonstrate superior learning from causal explanations of why events occur relative to descriptive accounts of what is occurring, live commentators predominantly employ the latter format – because detailed real-time causal explanations demonstrably increase cognitive load to a degree that impairs comprehension (Robertson et al., 2021). This finding imposes a practical constraint: the analytical depth that renders AI-generated insights valuable in post-match contexts constitutes a liability in live broadcast environments where viewer attention is divided. Complementary evidence from audience research on win prediction displays during League of Legends streams indicates that viewers evaluate predictive AI outputs not solely on accuracy but also on their contribution to narrative tension – preferences that favor predictions that maintain match uncertainty over those that are merely statistically correct (Wang, 2023). Together, these findings indicate that broadcast AI tools require a design logic distinct from that of analytical AI systems: one calibrated to narrative pacing and cognitive load management rather than to model performance metrics.

The production automation subgroup examines the application of AI to broadcast labor, where automated systems are progressively employed to replicate or supplement the functions of skilled human operators. The Observer framework for StarCraft II learns from recorded human observer behavior to automate in-game camera selection, achieving 56.9% behavioural similarity to human decision-making and outperforming rule-based alternatives (Bae et al., 2025). Highlight detection in League of Legends matches is addressed by the DENAN network, which learns spatiotemporal dependencies from match footage to generate tournament highlight reels without manual editorial intervention (Wan et al., 2022). At the level of commentary generation, the LoL-MDC tool compresses large-scale game log data into formats compatible with large language model (LLM) processing, enabling automated generation of match summaries and strategic commentary while circumventing input token-length constraints (Kim et al., 2025). A parallel line of research employs convolutional neural networks to extract game event sequences and classify ability readiness states from broadcast video footage – enabling statistical analysis for tournament organizers who lack programmatic access to internal game data (Luo et al., 2019; Eichelbaum et al., 2018).

The audience behavior subgroup examines the viewer dimension of streaming platforms through NLP analysis of chat data as a proxy for audience engagement and community dynamics. A BERT-based model trained on 18 million Finnish Twitch messages classifies chat content into original viewer commentary, emoji spam, copypasta, and bot commands, enabling researchers and platform stakeholders to isolate substantive audience feedback from high-volume data streams (Lindroos et al., 2025). Transfer learning from toxicity detection models trained on Twitter data demonstrates practical effectiveness for real-time Twitch chat moderation despite platform-specific lexical variation, indicating that cross-platform NLP transfer is viable for community management at scale (Gao et al., 2021).

A tension persists across the domain that individual studies have not fully resolved: the most analytically sophisticated broadcast tools – including interpretable predictive models, win condition narratives, and real-time SHAP visualizations – are simultaneously the most cognitively demanding for live audiences. The production automation strand moves in the opposite direction, prioritizing seamlessly integrated and cognitively unobtrusive outputs. Productive integration of these orientations – delivering analytical depth through production designs that actively manage rather than disregard cognitive load – represents an important agenda for future research.

6. Social aspects, communication, and natural language processing. Research in this domain examines esports as a social and cultural phenomenon, employing computational and qualitative methods to investigate how communities form, communicate, and contest meaning around competitive gaming. The literature is organized around two principal directions: the application of natural language processing (NLP) tools to map public discourse and sentiment across social media platforms, and qualitative and conceptual examination of the ethical, identity-related, and socio-economic dimensions of esports communities.

The public discourse subgroup applies a consistent methodological toolkit – encompassing topic modeling, sentiment analysis, and large-language model-augmented classification – to datasets from Reddit, YouTube, and Twitter. A cross-study finding is that public discourse around esports systematically extends beyond the boundaries of gaming itself, encompassing questions of cognitive development, social identity, cultural legitimacy, and economic participation. Analysis of StarCraft-related Reddit discussions reveals that community discourse encompasses emotional resilience and the transfer of competencies to non-gaming contexts alongside strategic content (Altindag & Balcioglu, 2025); comment analysis of YouTube videos addressing esports in the metaverse identifies immersive experience and technical constraints as the dominant public concerns, with health risks and accessibility barriers constituting a secondary thematic cluster (Mahmoud, 2025); BERTopic modelling augmented by GPT-4, applied to discourse surrounding the 2023 Asian Games, demonstrates that institutional inclusion in major multi-sport events accelerates esports legitimisation without resolving residual mainstream scepticism (Qian et al., 2025); and sentiment analysis of Reddit discourse concerning blockchain-based reward platforms indicates that positive community framing exerts a significant influence on user adoption intentions (Yadav et al., 2022). These studies are most productively read not as discrete findings but as a cumulative portrait of an industry actively negotiating its cultural status – simultaneously asserting institutional legitimacy, managing persistent stigma, and integrating into mainstream sport and entertainment structures.

The ethics, identity, and socio-economics subgroup addresses dimensions of esports community life that resist quantification and are correspondingly underrepresented in a domain dominated by predictive and classificatory modeling. Discourse analysis of the SaltyBet platform – in which viewers place wagers on matches between AI-controlled characters – reveals how communities construct shared interpretive frameworks around the unpredictability of AI behavior, generating an entertainment context organized around irony and collective spectatorship rather than competitive identification (Summerley & McDonald, 2025). Conceptual scholarship on the metaverse as a site for advancing diversity, equity, and inclusion in sport identifies virtual environments as potential structural equalizers that can reduce the physical, geographic, and economic barriers that constrain access to traditional athletics (Cunningham & Ko, 2025). A philosophical analysis of esports in the context of advancing AI argues for a reconceptualization of competitive values as the boundary between virtual and physical sport becomes increasingly permeable, raising questions of digital ethics that technical research programs have yet to systematically address (Xu, 2023). Economic analysis of the Overwatch League reveals a behavioral labor market dynamic – physical attractiveness predicts contract acquisition probability, but functions as a negative hiring signal in high-performing teams when unaccompanied by competitive results – demonstrating that esports labor markets reproduce and in some instances amplify biases documented in traditional sports industries (Babin et al., 2024). Collectively, these contributions perform an analytical function that the computational subgroup cannot: they interrogate the normative assumptions and structural values embedded in the institutional arrangements that NLP-based studies take as empirical givens.

A productive tension exists between the two subgroups that the literature has yet to address systematically. Public discourse studies treat community sentiment as a datum to be measured; ethics and identity studies treat community norms as social constructions to be critically examined. These orientations are complementary rather than mutually exclusive, and future research would benefit from methodological integration – employing computational tools to identify discourse patterns at scale while applying qualitative and theoretical frameworks to account for why those patterns assume the forms they do. A further limitation applies to the subfield as a whole: the predominance of English-language datasets systematically underrepresents the world's largest esports markets in East and Southeast Asia, where community discourse patterns, platform infrastructure, and cultural orientations toward competitive gaming differ substantially from the Western contexts that dominate the reviewed corpus.

7. Business, marketing, and economics. Research in this domain applies quantitative and analytical methods to esports as a commercial ecosystem, examining how AI and machine learning tools can optimize revenue generation, inform marketing strategy, and illuminate the economic structures – including labor markets, investment platforms, and fan engagement mechanisms – through which the industry operates. The literature is organized around three directions: commercial performance optimization, marketing effectiveness, audience engagement, and the economic organization of the esports industry.

The commercial optimization subgroup demonstrates that machine learning-based forecasting is both technically feasible and practically applicable across several esports revenue contexts. Regression models applied to a dataset comprising over 450 games – incorporating active player counts, prize pool volumes, and tournament frequency – indicate that the Huber Regressor, following hyperparameter optimization, achieves a near-perfect fit for merchandise sales forecasting while avoiding overfitting, thereby providing industry stakeholders with a data-driven foundation for revenue planning (Abu Sufian et al., 2024). In the digital trading card game segment, text-based features derived from card ability descriptions improve price prediction accuracy beyond that achievable from numeric attributes alone, confirming that a card's competitive utility – encoded in its rules text – constitutes a meaningful economic signal that conventional regression inputs fail to capture (Sakaji et al., 2020). Together, these studies establish proof of concept: esports revenue streams are sufficiently structured and data-dense to support predictive modelling, although both studies acknowledge that model performance remains sensitive to market volatility and meta-game shifts that training data cannot prospectively capture.

The marketing and engagement subgroup examines how esports organizations attract, retain, and monetize audiences, with particular attention to the roles of social media influencers and platform-specific content strategies. Nano-influencers emerge as effective communication intermediaries whose perceived authenticity amplifies positive user behavioral intentions while attenuating the negative effects of unverified trending information – a finding with direct implications for influencer selection and relationship management by esports brands (Yadav et al., 2022). The relationship between traditional sports fandom and esports engagement is characterized by genre specificity rather than uniform crossover: enthusiasm for sport simulation titles such as FIFA correlates positively with traditional football attendance and merchandise purchasing, whereas interest in structurally distinct esports genres – including MOBA and shooter titles – correlates negatively, suggesting that cross-promotional strategies must account for genre alignment rather than treating esports audiences as homogeneous (Lettieri & Orsenigo, 2020). At the content production level, generative AI demonstrates competence in interactive engagement formats such as audience polls but underperforms human-generated content in attracting non-follower audiences, indicating that AI-assisted content generation functions as a viable efficiency instrument for community maintenance rather than as a substitute for human creative capacity in audience acquisition (Ruiz-Pozo et al., 2025). Across these studies, the consistent implication is that marketing effectiveness in esports is determined less by channel selection than by the alignment between content authenticity, audience identity, and genre-specific community norms.

The economic organization subgroup examines the structural conditions governing esports as an industry, including tournament financing, player mobility, and the value-generation mechanisms of live events. Crowdfunding analysis of over 14,000 projects on the Matcherino platform identifies equitable prize distribution, major brand sponsorship, and game genre as the primary determinants of successful community fundraising, providing independent organizers with an empirical basis for campaign design (Xue et al., 2023). Social network analysis of the professional Dota 2 player transfer market reveals that player mobility is shaped by regional homophily, role-specific demand, and vertical mobility patterns analogous to those documented in traditional sports labor markets (Marchenko & Suschevskiy, 2018). The application of experience economy theory to esports tournament events highlights the role of immersive technologies – including virtual and augmented reality and large-format display systems – in transforming offline attendance into a sensory and affective spectacle that generates audience value exceeding that of the competitive content itself (Brock & Crawford, 2025). Generational analysis of 747 respondents confirms that attitudes toward esports as a sporting category and as an economic driver vary significantly by age cohort, with implications for industry positioning across demographic segments (Zdrilic et al., 2025). Bibliometric analysis situates esports within a decade-long structural transformation of the sports industry, in which AI and data analytics have generated novel business models and fan engagement mechanisms that traditional sports organizations are only beginning to integrate (Prabowo et al., 2026).

A limitation common to all three subgroups is the near-total absence of player welfare from the economic literature. Studies in this domain optimize revenue forecasting, marketing efficiency, and event experience design for organizers, sponsors, and audiences, while the working conditions, income distribution, career trajectories, and labor rights of professional players – the human infrastructure upon which the commercial ecosystem depends – receive no systematic analytical attention. This constitutes a structural gap that future scholarship in sports economics and labor studies is well positioned to address.

8. Dataset creation. Research in this domain addresses the infrastructural precondition for empirical progress across all other thematic areas reviewed in this chapter: without openly accessible, methodologically rigorous, and comprehensively documented datasets, advances in win prediction, player profiling, agent training, and audience analysis remain constrained by data availability rather than driven by analytical capacity. The literature is divided into three directions: datasets derived from professional match replays and telemetry, datasets designed specifically for MOBA game analysis, and datasets supporting NLP and behavioral research.

The replay and telemetry subgroup develops large-scale resources to extend access to esports research to scholars without direct access to game APIs or proprietary data infrastructure. SC2EGSet compiles 17,930 StarCraft II replay files from major tournaments since 2016, accompanied by open-source PyTorch tools for data retrieval and modeling, and explicitly targets research communities in AI, machine learning, psychology, and human-computer interaction simultaneously (Bialecki et al., 2023). The CDOPS dataset aggregates over one million rounds from professional Counter-Strike: Global Offensive tournaments into a resource designed for the study of coordinated human team dynamics under competitive pressure – a level of ecological validity that laboratory-based experimental designs cannot replicate (Duffy et al., 2025). The Professional Go Dataset extends esports data infrastructure to a title with an unusually long competitive history, compiling 98,043 games from 2,148 professional players spanning 1950 to 2021, with each move annotated using AlphaZero-based evaluation – enabling investigation of the longitudinal evolution of strategic thinking rather than solely outcome prediction or classification (Gao, 2022). Across all three contributions, the primary value lies not in the empirical findings but in the resource itself: each dataset materially reduces the barriers to entry for researchers who would otherwise be precluded from esports analysis due to data access constraints.

The MOBA dataset subgroup addresses two specific gaps in the broader data landscape: the underrepresentation of mobile esports and the scarcity of feature-rich datasets that support interpretable modeling frameworks rather than purely predictive ones. Two successive datasets from Honor of Kings provide the feature density required, respectively, to train the TSSTN model for simultaneous prediction and feature attribution (Yang et al., 2022) and to extend in-game event coverage sufficient for gradient attribution methods that explain model predictions rather than merely generating them (Yang et al., 2023). A methodologically distinct contribution generates a new category of League of Legends data – including champion positional data sampled at sub-second intervals, ability activations, and health and mana values – through computer vision and dynamic client instrumentation rather than API access, with the data generation pipeline made openly available (Maymin, 2021). Collectively, these datasets represent a deliberate effort to shift the analytical baseline of MOBA research from outcome prediction toward process understanding: from establishing who won to identifying why, and at which point in the match outcome became structurally determined.

The NLP and behavioral subgroup produces datasets designed to capture dimensions of the esports experience that are inaccessible to game log analysis: player engagement, audience dynamics, and community toxicity. A multimodal engagement dataset combining facial video recordings, gameplay footage, and minute-by-minute self-reported engagement data from 40 participants provides the annotated ground truth required to train automated engagement detection models – a resource with direct applications in game design, broadcast production, and player welfare monitoring (Guglielmi et al., 2025). The FinTwitchBERT dataset, comprising 18 million Finnish Twitch chat messages with a manually labeled subset of 7,529 messages annotated across four content categories, addresses both the linguistic specificity of gaming community discourse and the underrepresentation of non-English streaming platforms in existing NLP corpora (Lindroos et al., 2025). A toxicity detection dataset drawn from four Twitch communities spanning competitive, violent, and non-violent game genres provides the cross-genre variation necessary to evaluate whether classifiers trained in one community context transfer to others – a test that platform-specific datasets cannot support (Gao et al., 2021). The shared methodological commitment across these contributions is annotation rigor: each invests substantially in labeling reliability, reflecting the recognition that behavioral and linguistic ground truth is more difficult to establish than game outcome data and correspondingly more valuable when established with care.

Two structural limitations apply across the domain. Dataset coverage remains concentrated on a small number of titles – StarCraft II, Counter-Strike, League of Legends, and Honor of Kings – leaving fighting games, battle royale titles, and the rapidly expanding mobile esports sector substantially underrepresented. More fundamentally, the datasets reviewed are almost exclusively static snapshots of competitive activity at a given point in time. Longitudinal datasets tracking the same players, teams, or communities across multiple competitive seasons – capturing skill trajectories, strategic adaptation, roster transitions, and the effects of game patches – remain rare despite being essential for addressing the developmental and evolutionary research questions that the field is increasingly posing. The construction of such datasets requires sustained institutional commitment beyond the capacity of individual research projects, indicating a role for governing bodies, platform operators, and esports organizations in supporting data infrastructure as a collective resource for the research community.

AI in Esports as a Case of Digital Transformation in Physical Culture Education

The results of the literature review allow interpreting artificial intelligence in esports not only as a rapidly developing technological field but also as a concentrated case of broader changes that are becoming increasingly relevant to physical culture education. The reviewed studies show that AI in esports is applied to match prediction, player-performance analysis, behavioral profiling, physiological monitoring, automated agents, media support, social interaction analysis, business analytics, and dataset development. Taken together, these directions reveal a professional environment in which performance is no longer assessed solely through direct observation, practical experience, or conventional coaching judgment. Instead, it is increasingly mediated by data streams, predictive systems, and algorithmic models that influence both decision-making and performance evaluation.

From an educational perspective, this shift is significant because it signals a change in the structure of professional competence. In traditional models of physical culture and sport education, emphasis has usually been placed on methodology of training, motor development, physical performance, tactical preparation, and pedagogical interaction. The esports case demonstrates that these components remain important, yet they are no longer sufficient on their own in technology-intensive environments. Future professionals must also be able to interpret performance data, understand the logic and limitations of AI-based recommendations, critically assess automated outputs, and combine digital evidence with contextual professional judgment. In this sense, digital transformation should not be reduced to the simple introduction of new tools. It involves a deeper reconfiguration of how knowledge is produced, how performance is interpreted, and how professional action is justified in educational and training settings.

The esports environment is especially useful for analyzing these processes because it makes visible the growing instability of technologically mediated professional practice. In esports, strategies quickly lose relevance due to game updates, shifts in competitive balance, platform changes, and the emergence of new analytical models. This creates a field in which expertise is constantly challenged by volatility. Such conditions make resilience particularly important. In this chapter, resilience is understood not as a narrow psychological trait, but as a professional capacity to maintain meaningful and responsible action under conditions of rapid change, incomplete certainty, informational overload, and technological dependence. Read in this way, the case of AI in esports highlights that professional resilience in physical culture education increasingly depends on adaptability, readiness for continual learning, critical interpretation of digital evidence, and the ability to act when algorithmic systems provide support without offering complete certainty.

This interpretation also has implications for educational leadership. If the professional field is being reshaped by data-driven analysis, biometric monitoring, predictive systems, and automated support tools, educational leadership can no longer be limited to preserving established curricular models or reproducing conventional approaches to preparation. It must guide the redesign of programs in ways that reflect the changing relationship between human expertise and intelligent systems. This includes integrating interdisciplinary components into physical culture education, strengthening data and AI literacy, creating pedagogically sound approaches to digital monitoring, and preparing future professionals to work responsibly with ethically sensitive information. It also requires the creation of educational environments in which technological innovation is accompanied by critical reflection, interpretive caution, and an awareness of the risks associated with bias, opacity, and overreliance on automated decision support. In this respect, AI in esports can be read as a case within a broader case: it is a specific field of technological development that helps clarify the deeper logic of digital transformation in physical culture education under conditions of social uncertainty.

Conclusions

The conducted review of scientific publications enabled us to systematize the major directions of artificial intelligence application in esports and to demonstrate that this field extends far beyond isolated technical solutions. The analyzed studies demonstrate that AI in esports encompasses match-outcome prediction, player-performance analysis, behavioral modeling, autonomous and semi-autonomous agents, physiological and emotional monitoring, media support, social communication analysis, business analytics, and the creation of specialized datasets. Such findings confirm that esports has developed into a complex digital environment in which professional action is increasingly mediated by algorithmic systems, predictive models, and data-based evaluation procedures.

At the same time, the significance of this case extends beyond esports as a distinct industry. The review shows that AI integration in esports may be interpreted more broadly as a concentrated manifestation of changes that are becoming relevant to physical culture education as well. The analyzed body of research reflects a shift toward data-driven performance evaluation, technologically supported decision-making, continuous monitoring, and greater reliance on digital infrastructure. As a result, the case of esports provides an analytically productive basis for understanding how professional preparation in sport-related educational fields is being transformed by artificial intelligence and digital technologies.

This transformation has direct implications for the content of education. The case of AI in esports indicates that the preparation of future professionals in physical culture and sport can no longer rely exclusively on conventional training models centered on methodological knowledge and practical instruction. It increasingly requires data literacy, AI literacy, the ability to interpret performance analytics, and a critical awareness of the limitations and risks of automated systems. Equally important is the development of ethical sensitivity regarding biometric monitoring, behavioral profiling, and predictive modeling, since these tools influence not only performance enhancement but also privacy, fairness, and accountability in educational and professional practice.

The findings also clarify the meaning of resilience in digitally transformed environments. Under conditions of social uncertainty, resilience should be understood as a professional capacity to preserve reasoned action and adaptive judgment in situations shaped by rapid technological change, unstable digital platforms, shifting metrics, and incomplete algorithmic transparency. In this sense, resilience is linked to flexibility, critical thinking, continual relearning, and the ability to combine technological support with human responsibility rather than merely to endure external pressure.

Accordingly, educational leadership in physical culture education acquires a renewed role. It is increasingly associated with the ability to redesign curricula, strengthen interdisciplinary preparation, create ethically responsible models of technology use, and support learners' readiness to act in uncertain and rapidly changing professional conditions. From this perspective, the case of AI in esports helps illuminate a broader educational challenge:

how to prepare future professionals for environments in which innovation, uncertainty, and algorithmic mediation are the norm.

Recommendations

In light of the analyzed case, several practical directions may be proposed for the development of physical culture education. First, it is advisable to update the content of educational programs by incorporating topics related to digital analytics, interpretation of performance data, AI-assisted decision support, and the pedagogically appropriate use of intelligent systems in sport-related practice. Such renewal would allow future professionals to engage more competently with environments in which data and algorithms increasingly influence assessment and training.

Second, the training of specialists in physical culture and sport should be strengthened through interdisciplinary integration. The reviewed material suggests that contemporary professional preparation benefits from linking sport studies with pedagogy, psychology, digital technologies, and data analysis. This would make it possible to move from a narrowly instrumental understanding of technology toward a more comprehensive model in which digital tools are interpreted within broader educational, ethical, and professional frameworks.

Third, educational practice should include case-based and problem-based tasks that model situations of technological volatility, uncertain data, limited explainability of algorithmic outputs, and the need for responsible decision-making. Such tasks may contribute to the development of professional resilience by helping learners act thoughtfully in the face of change rather than merely reproduce stable routines.

Fourth, particular attention should be paid to preparing educators and academic leaders for the responsible governance of digital transformation. This includes awareness of privacy risks, algorithmic bias, data ethics, transparency, and the limitations of monitoring systems. The introduction of AI into educational and sport-related environments should therefore be accompanied by explicit ethical guidance and reflective pedagogical strategies.

Finally, further research appears promising regarding the transferability of the practices identified in esports to broader fields of physical culture education. It is worth examining which AI-based approaches can be meaningfully adapted to the preparation of coaches, physical education teachers, sport analysts, and other professionals whose work is increasingly influenced by digital monitoring, predictive systems, and data-supported forms of professional judgment.

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