applied sciences

Review

Esports Training, Periodization, and Software—A Scoping Review

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Abstract: Electronic sports (esports) and research on this emerging field are interdisciplinary in nature. By extension, it is essential to understand how to standardize and structure training with the help of existing tools, developed over years of research in sports sciences and informatics. Our goal for this work is to review the available literature in esports research, focusing on sports sciences (training, periodization, planning, and career stages) and software (training tools, visualization, analytics, and feedback systems). To verify the existing sources, we applied the framework of a scoping review to address the search from multiple scientific databases with further local processing. We conclude that the current research on esports has mainly focused on describing and modeling performance metrics that span over multiple fragmented research areas (psychology, nutrition, informatics). However, these building blocks have not been assembled into a well-functioning theory of performance in esports by, e.g., providing exercise regimes or methods of periodization for esports.

Keywords: esports; sport science; periodization; training; gaming; competitive gaming; review; human–computer interaction

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1. Introduction

Esports has proven to be a growing area of interest. This interest is not universally spread between varying disciplines. Gaming, esports, and interactive computer-simulated environments seem to be well established in the area of psychology [1–4]. Such psychological factors are sometimes related to the physical characteristics of esports [5]. Finally, comprehensive reviews relate traditional sports to esports and verify biopsychosocial factors holistically [6]. The same can be said for the broad information and communication technologies area of research, where simulated environments help in robotics and AI research [7]. Because of this, research on gaming and esports that deals with players at the height of their abilities is crucial. After all, in between areas of science, we can identify the algorithms, information systems, and data-based visualization tools that can support effective high-performance training in gaming and esports [8].

However, some distinct parts of sports sciences are seldom investigated in the context of esports. In traditional sports, topics such as training stages, periodization, stimuli/exercise selection, and control are well defined within the area of sports theory [9,10]. Let us assume that one would like to start strength training—there are multiple well-described methods for progression, rest times, and which exercises are best for this goal [11,12]. Similarly, researchers in sports define techniques that aim at improving regeneration through active and passive means [13,14]. In esports, it currently seems that there are no well-defined exercises, no definitions for intensity and load, and no way to test or verify progression quickly and assess it against actual in-game performance.

While gaming and esports are areas where data are abundant and relatively easy to access by anyone with computer skills [15–18], we seem to know nothing about the internal workings of this area. Essential information on properly structuring esports training from start to finish remains to be discovered and made available to the broader community. There are limited readily available tools that assist in periodization and uncovering what kind of training structure is optimal for various game genres.

The ability to achieve the highest sports results is a derivative of a well-functioning and properly planned—and broadly understood—sports training system. According to the model's assumptions, it consists of the subsystems forecasting, training, recovery and competition, qualification for sports, infrastructure and material support, and coaching staff. Therefore, it can be stated that only comprehensive solutions enable the achievement of sports mastery in every discipline [9].

We perceive esports as a field that is expanding very fast, with many groups of interest and stakeholders, mainly players, media, tournament organizers, and others [19–21]. Games provide an ever-changing environment that may be impossible to research effectively in pursuit of a comprehensive model of training at the highest level of play [22–24]. What if some of the skills that the players work for are instantly outdated by a new game release? In that case, we would like to emphasize the fundamental knowledge of exercises, scheduling, planning, and periodization that can be applied to any game.

Research on esports is fragmented by the very nature of this phenomenon. Games differ from one to another to varying degrees. Such differences include the required mechanical skills, game rulesets, and display methods. Existing works have described some genre differences; a non-exhaustive list of genres and game examples is as follows:

(1) First-person shooters (FPSs), e.g., Counter-Strike, Call of Duty, Overwatch, Valorant, and others;
(2) Real-time strategy (RTS), e.g., StarCraft 2, Warcraft 3, Age of Empires, Stormgate, ZeroSpace;
(3) Role-playing games (RPGs), e.g., The Witcher, The Elder Scrolls, Cyberpunk 2077, Fallout;
(4) Multiplayer online battle arena (MOBA), e.g., League of Legends, Dota 2, Heroes of the Storm;
(5) Fighting games, e.g., Tekken, Street Fighter, Mortal Kombat, Super Smash Bros;
(6) Rhythm games, e.g., Guitar Hero, Beat Saber, Dance Dance Revolution;
(7) Card games, e.g., Hearthstone, Magic: The Gathering;
(8) Sports games, e.g., Rocket League, FIFA, NBA 2K, Madden NFL.

In theory, any game can be considered an esport if it fulfills certain criteria [25–27].

Our goal for this work is to review the available literature in esports research, focusing on sports sciences (training, periodization, planning, and career stages) and software (training tools, visualization, analytics, and feedback systems). We view works with potential for practical application in facilitating esports training as of particular interest. To fulfill our goals, we have formulated the following research questions:

RQ1: *Since when has there been a steady increase in academic interest (expressed in the number of scientific publications) in the topic of esports?*
RQ2: *What aspects of esports training have been the subject of scientific research and can they be described by models used in sports theory?*
RQ3: *What types of software have been created to support esports training?*

2. Methods

In preparation for our scoping review, we followed the PRISMA guidelines. Precisely, we followed the PRISMA extension for scoping reviews and its related checklist. To conform with the scoping review standards, we manually collected data from the following scientific databases:

(1) ACM Digital Library;
(2) IEEE Xplore;
(3) Scopus;
(4) Springer Link;
(5) Web of Science.

For further processing, we leveraged the Python package "litstudy", offering a suite of tools for working with literature-based workflows [28].

2.1. Search Strategy

In our efforts to perform a comprehensive search, we prepared specific inclusion criteria before searching the scientific databases. Based on our goal, we decided to include all esports-related works published and available in scientific literature databases, focusing solely on works written in English. The search was constrained by the following query "(esport OR esports OR e-sport OR e-sports)" due to the varying naming used across the esports academic landscape. Later, all of these records would be filtered based on the inclusion criteria to fit the scope of our research goals. We set the search cutoff date at 15 June 2024.

2.2. Data Processing and Inclusion Criteria

Due to the overhead of defining complex queries in varying scientific search engines, we performed the rest of the analyses locally by leveraging the Python programming language and custom processing scripts with the "litstudy" package [28]. We ran automatic deduplication on the entire dataset from multiple databases to identify articles for further processing. Further processing warranted removing all of the works without stated authors, and we found that such works were most often article collections. Additionally, we filtered out all articles that were not in English or contained "l'esport" in the title, abstract, or keywords.

Similarly, to ensure that all of the documents considered research on esports, the following keyword search was conducted: esport, esports, e-sport, e-sports, electronic sports, e-sports, pro-gaming, and professional gaming. Given the interdisciplinary area of esports research, our inclusion criteria were split between two interest groups: One dealing with informatics, and the other with the area of sports sciences. Two groups of keywords were defined: (1) tool, data analysis, data science, dataset, machine learning, artificial intelligence, visualization; and (2) training, performance, cognitive training, neurofeedback, periodization, plan, and sport science. One caveat was that articles with the word "training" could have been found in both groups due to the word's broad meaning and its use in the context of "neural network training".

Finally, we merged both document sets with automatic duplicate removal. In the end, we reviewed the remaining articles and manually selected the most applicable works to answer our research questions. The entirety of the process is visualized in Figure 1.

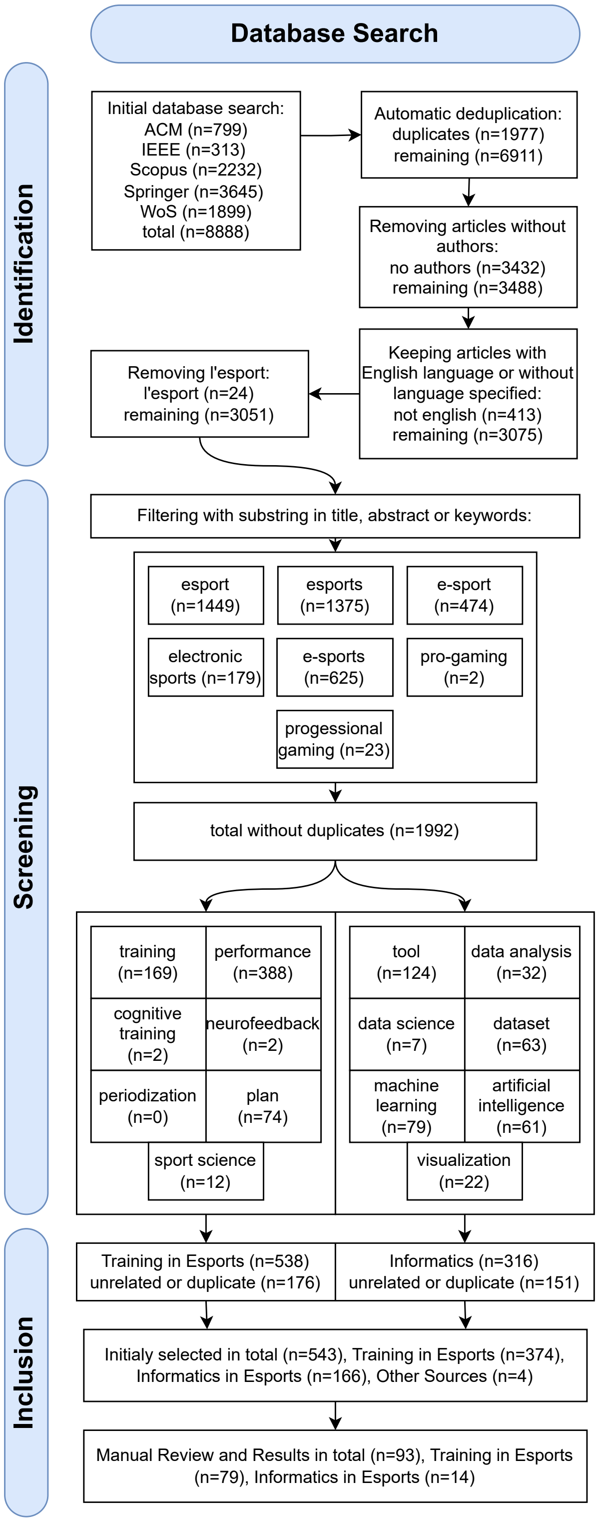

Figure 1. Scoping review article processing.

3. Results

While sources exist on esports curricula, their contents, and how to introduce esports into progressively more domains in addition to entertainment, more knowledge is still needed on how to structure esports training to facilitate the best possible individualized progress for esports players. Is it even possible to create a curriculum that could prepare coaches when there is no information on how to optimize training regimes and develop upcoming esports athletes [29–31]? A visual representation of the entire dataset is presented in Figures 2 and 3. The increasing frequency of publishing works related to esports is clearly visible since 2015; the lower number of published works in 2024 is due to the cutoff date of the search, as described in Section 2. Additionally, most articles were written by one, two, or three authors, as seen in Figure 3. This depiction shows the relatively low number of authors working in smaller teams in the area of esports (mean 3.16, median 2) as compared to the reported mean of about 4.3 to 4.6 and median of 4 authors observed for example in sports medicine journals [32].

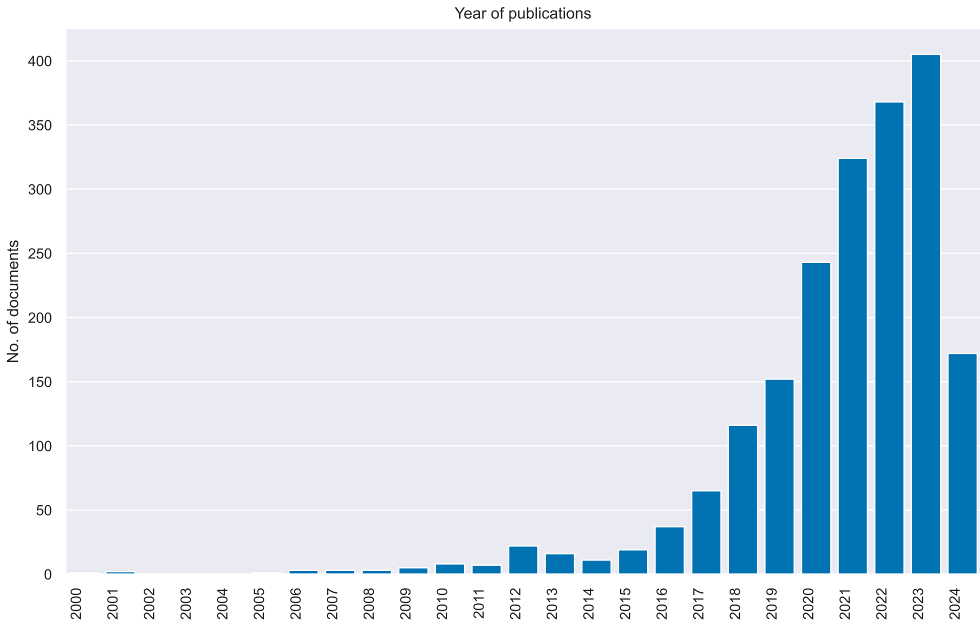

Figure 2. Year of publication histogram.

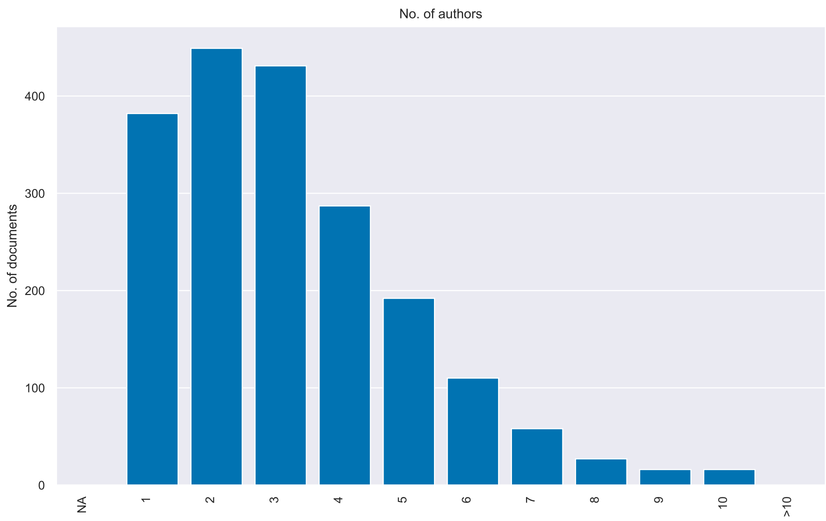

Figure 3. Number of authors histogram.

3.1. Training in Esports

Some authors have conducted work assessing how much time esports players devote to training [33]. According to their work, the average training time of elite esports players per day is 5 h and 28 min, of which just over 1 h is related to typical physical training. Others reported far longer training times—as much as 9.34 ± 1.12 h a day [34]. Notably, the researchers set the criteria for selection into the test as the player requiring an esports license and representing their country in international competitions. There are also known cases where players train 12–14 h a day, although some of this time might have been devoted to team meetings, video analysis, and strategic discussions [33].

However, others have shown that people who train more than 14 h a week have significantly shorter visual reaction time and better accuracy than those who train below the established limit of 14 h/week [35]. Moreover, both indicators mentioned above were improved due to supplementation/intake of 3 mg/kg of caffeine, as confirmed by some studies [36,37]. Improving reaction time is also possible by using appropriate training methods and tools. Ref. [38] claim that reaction speed when using an effective prompt is significantly faster than when the prompt is invalid. Additionally, some authors have drawn attention to the need to use increasingly specialized training methods in esports [39]. Their topical review considered esports optometric factors such as screen time and digital eyestrain, visual skill demands, and perceptual–cognitive skills such as visual attention. The problem of a comprehensive approach to esports training can be seen in the work of [40], who focused on nutrition, lifestyle, and cognitive performance in esports athletes. They demonstrated that esports athletes consuming the recommended amount of protein, riboflavin, phosphorous, vitamin B12, and selenium performed significantly better over the 18 core NTx (cognition via 3-dimensional multiple objects tracking test (3DMOT) via Neurotracker X (NTx) software) sessions than those that did not meet the recommended amounts.

3.1.1. Esports and Gaming: Mental Training

Within all the publications that qualified for this review, 44 referred to training aimed at developing the specialistic capabilities of esports players, i.e., those directly related to game achievements and performance. Among the selected works, the primary purpose of the research was to identify the length and frequency of training (playing games). Additionally, 12 works drew attention to the need to use imagery or mental training to improve performance. Nine of twelve articles were unavailable for access without payment and were not reviewed further. Among the available articles, one dealt with brain–computer interface (BCI)-controlled motor imagery training, confirming its positive impact on performance in experimental settings [41]. In other cases, authors focused on explaining the applied model of imagery [42]. Finally, as the authors explain how existing techniques like layered stimulus response training (LSRT) can be leveraged in the case of esports, they need to verify the technique's efficiency in practice [43].

3.1.2. Physicality of Esports

Works on physical training in preparing esports athletes constituted the second most extensive set, with n = 18. This category also included works that focused on the quantitative and qualitative descriptions of players' physical activity and performance. Two of these eighteen articles were only available with further payment and could not be manually reviewed. Among other studies, one piloted an 8-week intervention based on introducing physical exercise to the training routine of high-level esports players. The researchers found that physical activity reduced players' fatigue perception and improved their physical performance [44]. Among adolescents, most of the respondents declared that they were physically active. However, it is unclear how many of them were active esports players and not recreational gamers [45].

Similarly, other authors investigated the attitudes of grassroots players towards physical activity [46]. Finally, other authors found that 6-min active breaks during practice sessions improved executive functions in players [47]. Generally, research seems to recognize and describe the physical aspects of esports [48]. Despite that, there is no clear evidence of leveraging physical training to improve esports performance.

On the other hand, other studies dive into the medical aspects of injury prevention and pain within competitive gamers and esports athletes [49–51]. The authors underline the importance of medical attention in the case of esports athletes to prevent early retirement and financial consequences [52]. Research in this direction uncovered that players tend to train less when in the presence of pain [53].

Some authors found that short sprint exercises positively impacted cognitive performance in amateur esports players [54]. Studies performing systematic reviews found that despite multiple articles reporting on esports players' engagement in physical activity, their reported activity was only a small portion of the main training components [55]. In other cases, players were described as a low-active group, while high-level professionals were found to have higher levels of physical activity [56]. The vast majority of studies focus on self-reported data for physical activity levels. While this paints a picture of physically active esports athletes, such methods do not provide an entirely objective view of the situation.

Some works considered this limitation and outfitted their respondents with accelerometer devices to asses their physical activity levels. They found that participants overstate their physical activity [57]. It seems that most of the players engage in physical activity as a way to stay healthy rather than to improve their performance [33]. Finally, physical activity is recognized as a potentially fruitful avenue of research for esports [58].

3.1.3. Various Factors of Esports Performance

Twelve publications concerned the impact of reaction time on gameplay results or broadly understood game performance. The analyzed works examined the impact of various methods and techniques for improving reaction time and the impact of equipment, e.g., mouse weight. Twelve publications concerned nutrition and supplementation of various products and nutrients. Most articles assessed what and how high-performance players eat, including supplementation of selected ingredients, e.g., caffeine, which affects their performance during competition. It is also worth emphasizing that in individual publications it was possible to recognize opinions about an insufficient level of knowledge about nutrition in esports [59].

Eighteen works concerned health and mental health. The analyzed works usually presented opinions on the perception of one's health condition on the results achieved and an analysis of esports players' opinions on whether mental and physical well-being affects the improvement of gaming results. Moreover, the published works included information on virtual athletes' healthy lifestyle habits. Sleep is also essential for health, and its impact on performance has been described in 10 studies. Moreover, these articles tried to characterize the best players' sleep length and quality of sleep.

Unfortunately, no publications regarding the periodization of training on esports were found. However, one work comprehensively described the training structure and presented a performance model [60]. Some research suggests a strong need to create detailed structures and training methods based on real sports achievements [25]. A similar position was expressed by more authors, who uncovered that organized training and its structure could influence the performance of esports athletes and could also improve their health [61].

3.2. Informatics in Esports

Esports change constantly due to software patches, in-game changes, and advances in the technology used in game design [62,63]. It is clear that esports, in their essence, are fully automated sports; each of the peripheral devices acts as an interface for the computer, where the rules of competition are implemented within the simulated environment. Due to this, access to data is abundant. There are multiple available datasets spanning game genres and game titles. Some focus on tournament games [64], or ladder games [65] in StarCraft 2. Others work with games that could be considered board games and computer games [66]. Some publish video data from League of Legends [67,68], while others deal with Counter-Strike [69]. There are undoubtedly many of them. These datasets are part of the vital ecosystem of infrastructure that is needed to develop the field of esports informatics. Creating automated systems with capabilities to reliably provide immediate feedback to the players, coaches, or other stakeholders could assist lower-tier players in their development.

Moreover, multiple works define data visualization experiences for gaming and esports. These tools provide technology that helps to see the often nuanced in-game environments in an easily digestible way [70,71]. Post-game reviews can be crucial in understanding the pain points in performance; leveraging of this information by experienced players and coaches should be the ultimate goal [72]. Despite that, such implementations are also applicable to other uses, e.g., betting [73] or spectatorship [74]. In the end, research exists on leveraging the varying algorithms to assist humans in defeating other human players, defeating humans as agents/bots, or playing against other agents/bots [75].

4. Discussion

4.1. From Sports to Esports

We raise the question of whether transferring the already established structures, ideas, and systemic solutions [10,76] to electronic sports is possible. If so, should all of these elements be copied and transferred to virtual competition? Our primary task is to focus on finding an appropriate system for selection and recruitment, a well-planned multi-year training process with a programmed duration for each training stage, appropriately distributed periodization of smaller training cycles, the choice and application of the most suitable methods, forms, and means of training, the proper proportion between training and rest, and the development of the psychomotor and cognitive abilities of future esports champions. With the help of IT tools, it is also possible to introduce an appropriate system for training control and analyzing tactical actions during sports competitions. This would contribute to creating a model of a champion in esports.

Coaching staff highly seek iterative processes of improvement in sports. Out of the 374 articles related to training in esports, 79 reports were considered the most related to the topic. However, juxtaposing the content of these publications with the "prognosis, program, plan" model, as adapted from [9], a very selective approach was noticed, focused mainly on single parameters or factors that are not a reference to a complete system of training in esports. This iterative system is presented in Figure 4; we include our general experience-based mapping of the available literature in this depiction. This suggests to us that the current state of knowledge on training in esports is underdeveloped. Such a knowledge gap leaves the immense esports industry without the fundamental understanding required to develop future champions.

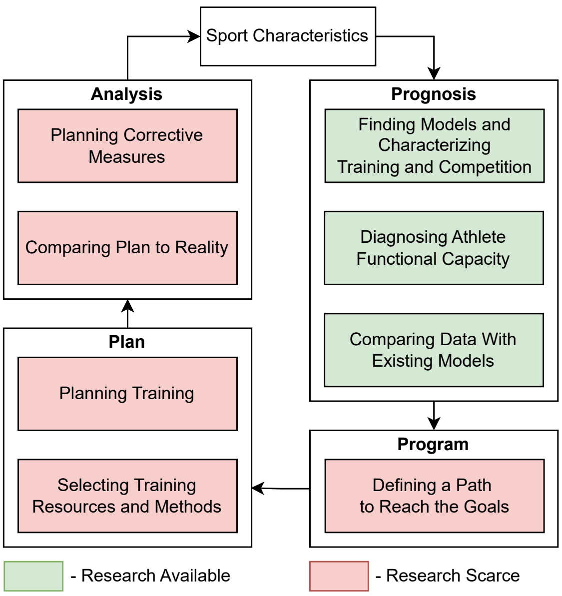

Figure 4. Training model, "prognosis, program, plan", adapted from [9].

4.1.1. Training Stimuli in Esports

In widely known traditional sports, competitive goals determine the training process. This goal is often to achieve the best possible performance or tournament placement. Reaching mastery in any sport requires substantial training time across a wide array of controlled stimuli. Psychophysiological adaptations accompany the effective use of these tools; the so-called “form” comes as a result, and the outcome should be a high competition placement. Due to the complexity of these processes, working with sports requires the right approach and time for these adaptations to occur. Sports sciences and theoretical approaches guide the optimal time to begin training in various sports.

4.1.2. When to Start Training?

First, there are three types of traditional sports: early, normal, and late. Involvement in early sports often starts at just 3–4 years old for upcoming athletes. In this category, the highest performance is reached at 15–17 years of age, e.g., gymnastics, swimming, tennis, and others. Sports assigned to the “normal” category start at 8–10 years old. These are, for example, track and field, football, volleyball, and others, where the highest performance comes at 18–21 years of age. Finally, in late sports, the start of training is marked at 13–14 years old, and the highest performance comes after 22 years of age, e.g., combat sports, weightlifting, long-distance running, and others [77].

Secondly, the right time to start training is bound to the anthropologically set level of development/maturity. Molding of physical abilities, and especially coordination skills, may be subject to “critical times”, i.e., intervals at which it is best to apply certain stimuli to achieve maximal adaptation. Not leveraging this timing can curtail the ability of an athlete to adapt further and reach their full potential [78]. These natural capabilities act as a base for formulating and defining stages in sports training; by extension, these stages include recommendations for methods, forms, and training means. Standardized stages of sports training and development emphasize the educational and fostering character of psychophysical capabilities through play. In this regard, it is essential to remember about other areas of life and other sports, as overspecializing in one area may not be beneficial. They primarily consider that in the process of anthropological development, the final sporting activity may not have been selected.

In their studies on esports training and physical exercise, other authors obtained data from a sample of 115 professionals and high-level esports players, with an average age of 20.8 years [33]. Motivation in amateur esports players was studied by [79]—the average age of people participating in virtual competition was also similar and amounted to 20.15 years of age. When looking at amateur players who do not necessarily compete in esports, 24 fans at the Intel Extreme Masters (IEM) 2018 esports world championship in Katowice were asked about their experience. This indicated that the average age of experience in gaming is, on average, ten years. The average age of participants was 19 years old. This indicates the average experience to be nine years. Participants also declared their first competition to have been at about 14 years of age [80].

4.1.3. Approaching Long-Term Development

Thirdly, selecting the optimal training load required to reach mastery is essential. According to [81], it takes roughly 10,000 h and at least ten years of training to be an expert in a given activity. Of course, this does not precisely reflect reality, as everything depends on the athlete’s selected sport and other individual features [82]. In sports theory, when viewing training as a process, stimuli are evaluated and planned within a compositional structure, as shown in Figure 5.

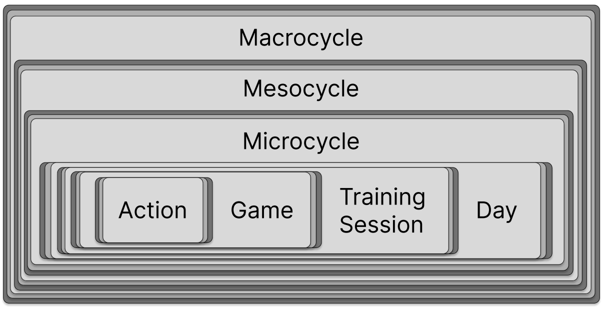

Figure 5. Compositional structure of sports.

Current concepts regarding the development of adolescent athletes are aimed at long-term athletic development (LTAD). They show multiple advantages while minimizing the possibility of a premature career ending [83,84]. The LTAD model consists of solutions for anyone, not only elite athletes but also people who engage in sporting activities as a base for their fitness and wellness [85]. This model is built around seven stages of sports training:

(1) Active start;
(2) Fundamental;
(3) Learn to train;
(4) Training to train;
(5) Training to compete;
(6) Training to win;
(7) Retirement/retraining [82,86,87].

In 2014, the United States Olympic Committee, along with their national administration, used the rules of LTAD to create the American Model of Development. In their work, they defined the following five stages:

(1) Discover, learn, and play (ages 0–12);
(2) Develop and challenge (ages 10–16 years);
(3) Train and compete (ages 13–19 years);
(4) Excel for high performance or participate and succeed (ages $\geq$ 15 years);
(5) Mentor and thrive for life [82].

4.1.4. Stimulus Effectiveness and Selection in Sports

Traditional sports have a system of selection that is often ruthless for children who develop late and do not provide immediate results for their clubs or teams. Looking at computer games and esports from the perspective of sports science and traditional sports could be beneficial. Playing into the well-defined stages of human development and "critical times", beginning esports training as soon as possible should be researched. This is primarily due to cognitive abilities and movement coordination development between 6 and 12 years of age. Similarly, it is said that socializing at age 11–19 is essential, and long hours of sedentary training could act contrary to this. We recommend intensive research into how the existing LTAD and other recommendations could be applied to successful esports development [88,89].

4.2. From Esports to Sports

New technologies, including simulated environments, virtual reality, and extended or augmented reality, do not function in a vacuum. Where there is a new technology, people innovate. Such technologies hold high potential in providing training tools for traditional sports, rehabilitation, and many more [90]. Creating specific training tools is possible, for example, designing a bow device to facilitate a virtual training of archery [91,92]. Additionally, as briefly described in Section 1, multiple game genres exist. Due to this, each game genre may offer multiple stimuli that should be recognized and ultimately used in the case of esports, as well as in traditional sports. For example, StarCraft 2 is a fast-paced, real-time strategy game facilitating fast decision making, multitasking, and resource control. On the other hand, Counter-Strike, as a first-person shooter game, requires short reaction times, aiming, and team coordination. Finally, card games like Hearthstone or Teamfight Tactics require strategic thinking, planning, and adaptability to randomness. These are just a few selected examples of different requirements placed on the players in gaming and esports.

Many advancements exist in the area of reinforcement learning. These systems are capable of beating human opponents in drone racing [7], Go [93], chess and shogi [94,95], StarCraft 2 [96], and Dota 2 [97,98]. What if they were used to provide fast and actionable feedback to human players? What are the limits of human performance with such assistance tools? Why not leverage these agents to detect and recommend action to enhance the human experience and plan training and educational efforts? Therefore, let us transition into the realm of optimizing artificial intelligence models to play games and define tasks to optimize the human player's performance.

This kind of model could consider not only immediate and short-term actions but additionally the long-term development of the player and many other players in the ecosystem. Aligning such systems with the existing knowledge in the theory of sports would mean creating a model that can assist with the following:

(1) Action-by-action, decision-by-decision feedback;
(2) Game-by-game feedback on tactics, strategies, and performance;
(3) Session-by-session feedback;
(4) Day-by-day feedback;
(5) Microcycle (weekly) feedback;
(6) Mesocycle (monthly) feedback;
(7) Macrocycle (yearly) feedback, and more!

Moreover, systems of this type should have the capability to match the closest and related exercises to alleviate any issues in the players' performance effectively. Another diagram assisting with the understanding of this proposed system is shown in Figure 6. Interestingly enough, the execution environment, as seen in Figure 7, adapts the ideas from reinforcement learning (RL). We view it as a middle-ground between the most basic model diagram of RL as described by [99] and how sports operate in reality.

Solutions of this kind are generally described as dynamic difficulty adjustment (DDA). Some researchers have found that DDA contributed to heightened engagement [100]. Similarly, when looking at platform games, researchers found that applying performance-based DDA and artificial neural network (ANN) DDA allowed players to achieve a more enjoyable in-game experience. Additionally, authors recommend integrating physiological sensors for further research [101]. In the end, the DDA research discussed here focuses primarily on heightening player enjoyment rather than optimizing player performance [102]. It does not seem that researchers are focusing on how to apply such systems in the long-term development of a human player with a complete overview of various metrics longitudinally. Similarly to the conclusions made by the authors of a study performing a systematic review on DDA [103], we urge researchers to attempt to apply DDA systems focusing on the structure of sports training as seen in Figure 5.

Despite the availability of many software implementations created for research purposes, we did not notice the use of such software in support of training as a popular phenomenon in esports. We are yet to see software systems fully integrated into esports training. We hope that such systems will leverage the longstanding knowledge as it exists in sports sciences and traditional sports [9,76,104]. Iterative development with user consults on applicability can shed light on what direction is most promising for training software development in esports. Solutions used in practice that focus on helping users achieve their goals can advance esports and traditional sports. On the other hand, the same issues are present in traditional sports. There are many Internet of Things (IoT) devices [105], sensors [106], and tests [107–109] capable of measuring athletes [110]. However, coaches are still battling against the ever-changing nature of athletes and their environments.

In the end, practical applications of the idealized systems from sports sciences still need to be applied in esports. While the traditional system defines iterative steps to control progress, we have yet to see much evidence for research on such systems in esports. On the other hand, we observe evidence of such systems in applied reinforcement learning. Due to the high availability of data and recent advancements in robotics and reinforcement learning, we view this research venue as incredibly fruitful and potent for using automated systems to assist in the training process. Creating automated and democratized tools for training in esports based on in-game and out-of-game measurement feedback systems could be a significant step forward in the development of esports athletes and the sporting industry as a whole.

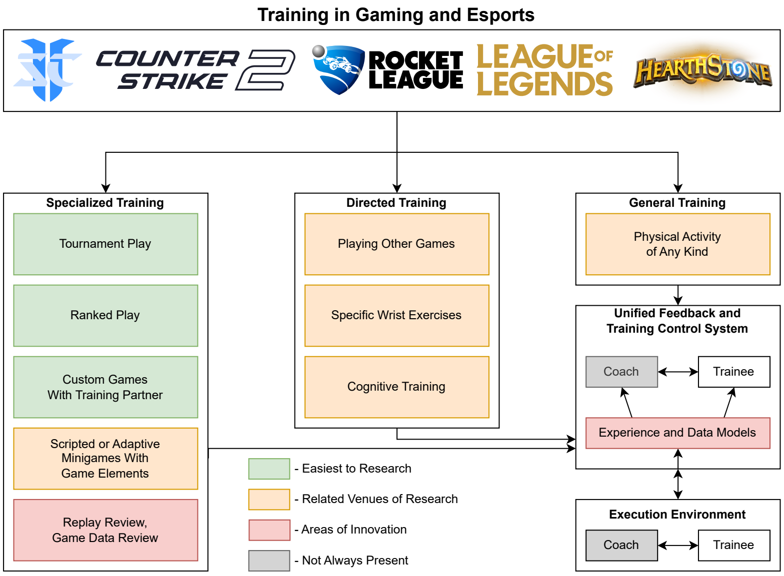

Figure 6. Model system of training in esports, partially adapted from [9]. Game logos attached for illustrative purposes.

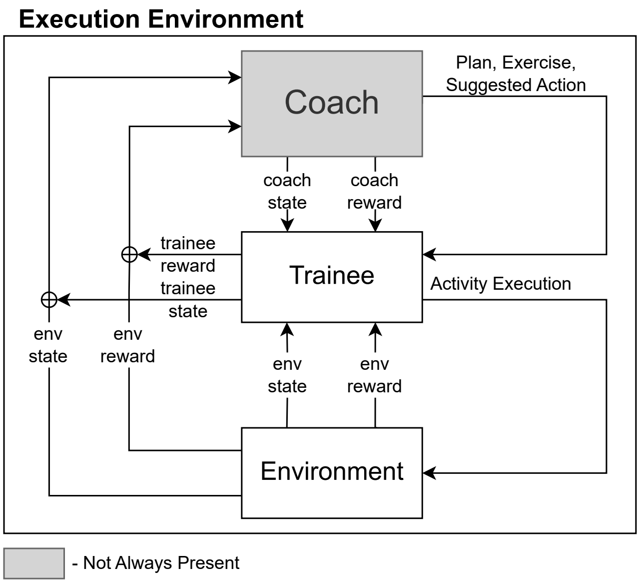

Figure 7. Model of an execution environment. Adapted from popular reinforcement learning explanatory diagrams.

5. Limitations

Despite our study being a comprehensive literature review, it has limitations. We acknowledge that we may not have used other scientific literature databases in Section 2. Due to the dynamic nature of esports, it is unclear if information on practical and effective training is not already present. Gaming and esports communities tend to share their experiences in online tutorials and pass them down through video streaming or peer-to-peer learning within smaller esports communities. We recognize that while we did our best to look for all of the materials concerning esports, it may be impossible to collect all of them at any given time due to the nature of the academic indexing. We might have missed some articles concerning esports and player development.

To sum up, the cutoff point for the materials under investigation was placed at 15 June 2024. Some of the more recent publications might not have been included in our review. This is apparent and visible in Figure 2. Additionally, due to the interdisciplinary nature of esports, some categories of articles may have overlapped. In other cases, articles that did not provide sufficient indexing information may have been omitted.

6. Conclusions

We conclude that the popularity of esports research, as measured by the number of published works, is growing steadily (**RQ1**). Sources on periodization, planning training, and specialized exercises are insufficient (**RQ2**). Moreover, the literature on data analyses, processing, and visualizations exists, with impressive solutions to work with major datasets. These topics are a part of the broader subsystem of training control. Despite that, there is limited information on their application outside of research (**RQ3**).

There is a need to start researching periodization of the training process in esports. The incomplete structure and inaccurate training characteristics in esports pose a considerable challenge for coaches and players. Therefore, organizing knowledge and filling gaps in the broadly understood esports training is extremely important, following the example of well-established and existing knowledge in traditional sports. We urge researchers from varying backgrounds to join forces to put all of the building blocks of a successful training system together and start working on validating specific exercises and training methodologies.

Unfortunately, due to the complex nature of esports encompassing all possible games, defining a standardized approach that would fit all of them may not be possible. We encourage researchers to recognize these differences and start validating exercises that could fit into the existing periodization frameworks by defining them as general, directed, or specialized in the context of their selected games. Additionally, some games are discontinued, and technology is deprecated; some training methodologies may not transfer to other games or game genres. Finding a way to conduct training in esports to create flourishing and long-lasting opportunities will be necessary.

Finally, it is tough to discern between studies that relate their findings to recreational gamers, competitive gamers, and esports athletes. Competitive play is not equal to esports performance. We urge researchers to clearly define their participant groups and the context of their research to make it easier to compare and contrast findings across studies, especially since all of the games have the potential to be played at a recreational level, competitive level, or professional level.

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Abbreviations

The following abbreviations are used in this manuscript:

BCI	Brain–computer interface
LSRT	Layered Stimulus Response Training
IT	Information technology
IEM	Intel Extreme Masters
LTAD	Long-term athlete development
RL	Reinforcement learning
DDA	Dynamic difficulty adjustment
ANN	Artificial neural network
IoT	Internet of Things

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