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Review

Digital twins in sport: Concepts, taxonomies, challenges and practical potentials

Tilen Hliš [*], Iztok Fister, Iztok Fister Jr.

Faculty of Electrical Engineering and Computer Science, University of Maribor, Koroska cesta 46, Maribor 2000, Slovenia

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A B S T R A C T

Digital twins belong to ten of the strategic technology trends according to the Gartner list from 2019, and have encountered a big expansion, especially with the introduction of Industry 4.0. Sport, on the other hand, has become a constant companion of the modern human suffering a lack of a healthy way of life. The application of digital twins in sport has brought dramatic changes not only in the domain of sport training, but also in managing athletes during competitions, searching for strategical solutions before and tactical solutions during the games by coaches. In this paper, the domain of digital twins in sport is reviewed based on papers which have emerged in this area. At first, the concept of a digital twin is discussed in general. Then, taxonomies of digital twins are appointed. According to these taxonomies, the collection of relevant papers is analyzed, and some real examples of digital twins are exposed. The review finishes with a discussion about how the digital twins affect changes in the modern sport disciplines, and what challenges and opportunities await the digital twins in the future.

1. Introduction

Nowadays, breaking the premise between the physical and virtual worlds can be done using digital twins. The Digital Twin (DT) concept is a replicated digital model of any device, product, or process. The history of DTs dates back in history, while, contemporary, they are used in the real world, where many applications were already developed. Indeed, DTs are, today nowadays, applied to several areas, for example, the medicine domain (Laubenbacher et al., 2024); aerospace engineering (Ferrari and Willcox, 2024), city planning (Batty, 2024), sport (Lukač, Fister, & Fister, 2022).

Since DTs are virtual replicas of physical assets, users can monitor realtime environments and perform various analyses. Data-making decisions are much more efficient, since they involve genuine, real-time data, which is crucial for efficient knowledge extraction from data. In many industries, it also allows users to design new products and digital replicas before producing a physical object, which also optimizes resources and costs. In Industry 4.0, and, later, in Industry 5.0, DTs can help optimize operations in production (Wagner et al., 2019; Leng et al., 2021; Lv, 2023). Also, in the recent era of global warming, they can help reduce carbon footprints during the optimization of processes (Ghita et al., 2021).

Sports are physical activities that numerous people perform several days per week, primarily to maintain health, well-being, and relaxation. At the same time, countless serious athletes compete in different sports competitions (Rauter, 2014). Modern Information Technologies (IT) are also entering the world of sports and revolutionizing how people, athletes, and trainers perform different sports. From the simple wristwatches, which were capable of measuring the heart rate in the late 90 s, then, later, with the smartwatches that could monitor more parameters (Chandel et al., 2022), e.g., GPS position, calories, and weather parameters, modern solutions emerged that can also give athletes advice during their training (Kamišalić, Fister, Turkanović, & Karakatič, 2018; Fister et al., 2019). The main stepping stone lies in the data, which forms the way to make decisions (Miller and Mork, 2013). Many decisions base on data investigated by intelligent data analysis methods and tools, among which we can count Machine Learning (ML) (Russell and Norvig, 2016); Computational Intelligence (CI) (Engelbrecht, 2007), and various processes and techniques under the umbrella of data science (O'Donoghue and Holmes, 2014). These methods can plan the sports training sessions (Fister et al., 2019), analyze the sensor data arising during sports training/exercises (Novatchkov and Baca, 2013), generate sports training routes (Rajšp & Fister, 2022), etc. Not long ago, the concept of DT was also introduced into sports in different realms, e.g., in the role of a personal assistant during sports training sessions (Lukač, Fister, & Fister, 2022).

* Corresponding author.
E-mail addresses: tilen.hlis@um.si (T. Hliš), iztok.fister@um.si (I. Fister), iztok.fister1@um.si (I. Fister Jr.).

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In the sense of the theory of sports training (Fister et al., 2019); the sports training consists of four phases: planning, realization (also implementation), control, and evaluation. The planning phase allows sports trainers to prescribe a training load, which needs to be overcome by an athlete during the implementation. In the realization phase, the response of the athlete on the prescribed load (i.e., physical stress) is controlled by the sport strainer using appropriate measuring tools. The realized sport training sessions are typically evaluated at the end of the training cycle using a performance analysis based on Machine Learning (ML) methods.

Recently, a vision of developing the universal Artificial Intelligence (AI) sports trainer emerged ubiquitously (Fister et al., 2019). These intelligent systems typically base on Knowledge Discovery from Data (KDD), and they are capable of performing automatic decision-making tasks. The final purpose of these automations is replacing the influence of the real sport trainers in those sports disciplines where this automation is possible (e.g., a personal fitness trainer). However, the DT is a necessary prerequisite of such systems, where its role is, especially, to cover the realization and control phase of the sports training. Obviously, in other, especially, team sports disciplines, their practical applications can be to help the real sports trainers in planning and evaluation phases as well (e.g., preparing and analyzing the strategy and tactic solutions for their opponents in football).

In this paper, we take a closer look at the DTs arising in a vibrant area of sports, sports training, human movement, and competition. Our goals are to review the current state of this research area, propose a taxonomy of DTs in sports, identify the main challenges and obstacles of this technology, and produce guidelines for creating new DTs.

Indeed, there exist already review papers from this domain. For instance, the review papers by Gamez Diaz et al. (Ǵamez Ḿıaz et al., 2020) and Pascual et al. (Pascual et al., 2023) have dealt extensively with the development and implementation of DTs in physical activities and human modeling, respectively. Gamez Diaz et al. focused on the DTs' role in coaching and fitness, particularly in providing personalized feedback, and enhancing training efficiency through edge computing and deep learning-based pose estimation (Ǵamez Ḿıaz et al., 2020). Pascual et al. provided a systematic review of human digital twins, emphasizing their applications in various domains, including sports, and highlighted the challenges in data integration and model accuracy (Pascual et al., 2023).

This review article is founded on knowledge from previous review articles in this field, where the authors have captured DTs in sports and attempted to construct new knowledge mosaics. The review papers of Ǵamez Ḿıaz et al. (2020) and Pascual et al. (2023) are the closest to our review paper. However, the advantage of our paper is that it tackles the actual state of DTs in sports, and proposes a new taxonomy that should be a stepping stone for developing new DTs in sports.

Additionally, our review aims to bridge the gap between the existing literature by proposing a novel taxonomy for DTs tailored specifically to sports, addressing both individual and team sports across various disciplines. Additionally, our work identifies the practical implementations of DTs, such as AST Monitor and DTCoach, which are highlighted for their advanced realworld applications. By providing a comprehensive analysis of DTs, our review offers deeper insights and future directions for integrating DT technology in sports more effectively.

The contributions of this paper are as follows:

- an overview is conducted of DTs in sport,
- a taxonomy is proposed for DTs in sport,
- the main DTs are identified in theory and practical use,
- future challenges are studied and opportunities for further use.

The structure of the remainder of paper is as follows: Section 2 reveals the fundamentals of DTs. The research methodology for assembling a collection of papers for extensive analysis is discussed in Section 3. In Section 4, a detailed analysis of DTs in sport is described, while the taxonomies of DTs in sport are appointed in Section 5. Real examples of DTs in sport are the subject of Section 6. Section 7 deals with the question of how the DTs change the modern sport disciplines. Challenges and opportunities are treated in Section 8, while the paper is finished with Section 9, where also the directions are outlined for future work.

2. Fundamentals of digital twins

A DT is a replicated digital model of any physical entity (i.e., device, product, or process) with the same behavior as the original ones. In Gartner's list from 2019, it belongs to the top ten strategic technology trends. The DT roots originated in 1960 from the National Aeronautics and Space Administration (NASA) Apollo program (Romero et al., 2020), within which space flights were simulated in the virtual environment during the various astronauts' training phases. With the advent of Industry 4.0 and Industry 5.0, the technology was integrated into unified models (i.e., smart factories) that drive product design, manufacturing, and cyber-security (Chen, 2021; Holzinger et al., 2024).

A concept of a DT is illustrated in Fig. 1, from which it can be seen that the DT integrates the physical and digital world with a complex data manipulation. Data which arise during the data acquisition phase by a physical entity are transmitted to its virtual counterpart. Before being used by the DT processing model, they need to be fused with data from external sources (e.g., external databases, or the Internet), and cleaned during an aggregation phase. Indeed, the DT processing model models the properties of the physical object. The majority of the DT applications needs a lot of services (e.g., Association Rule Mining (ARM)) that are incorporated into a DT processing model. The results of the DT processing model are represented in the action phase in different forms that serve to help decision-makers by accepting the complex decisions.

The architecture of a DT consists of more components, working interconnectedly between each other, which, thus, determines the workflow of data across those. The components of the typical DT are as follows (Fig. 2) (Patel et al., 2022):

1. data acquisition,
2. transmission,
3. data integration,
4. data preprocessing,
5. processing model,
6. services,
7. actions.

Interestingly, the first two components are devoted to sensing the physical world, while the last one affects it with actions. The third component integrates the physical world with the virtual one, while the next three represent an implementation of the specific DT.

The data acquisition component allows acquiring data from various Internet of Things (IoT) devices, sensors, mobile devices, and wearable devices, with which a physical entity is monitored. The acquired data are then transmitted to the DT using network services.

In general, the data integration component addresses problems of fusion of the acquired data from the physical world with data from external databases via different network interfaces. This component is devoted also for protecting the computing devices and sensitive data from ransomware attacks (Joshi, 2022).

The data preprocessing component provides that unstructured data from IoT sensors, as well as other structured and unstructured data from other external sources are transformed into a format, which can be understood and analyzed by computers and ML methods. In line with this, more data preprocessing methods can be applied, e.g., data cleaning, data transformation, and data reduction. The model consists of three sub-components, as follow (Joshi, 2022): (1) input data, (2) DT process model, and (3) output data. The input data is responsible for preparing unstructured data, either acquired from various sources, like IoT devices

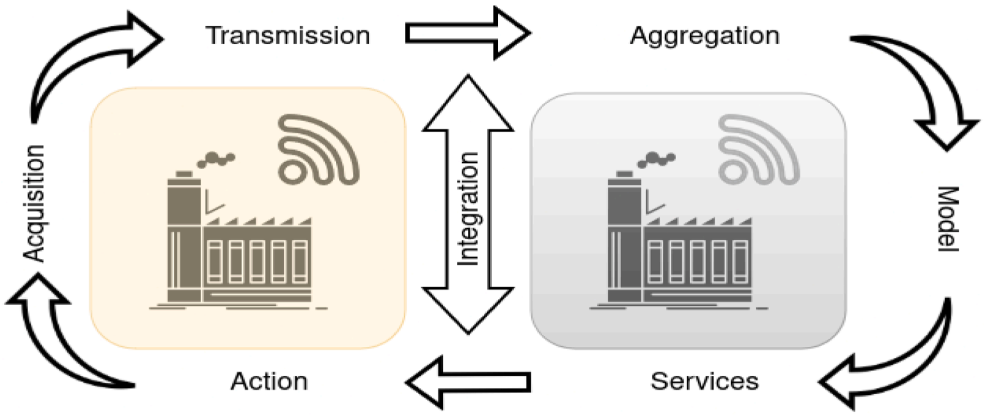

Fig. 1. Concept of a digital twin.

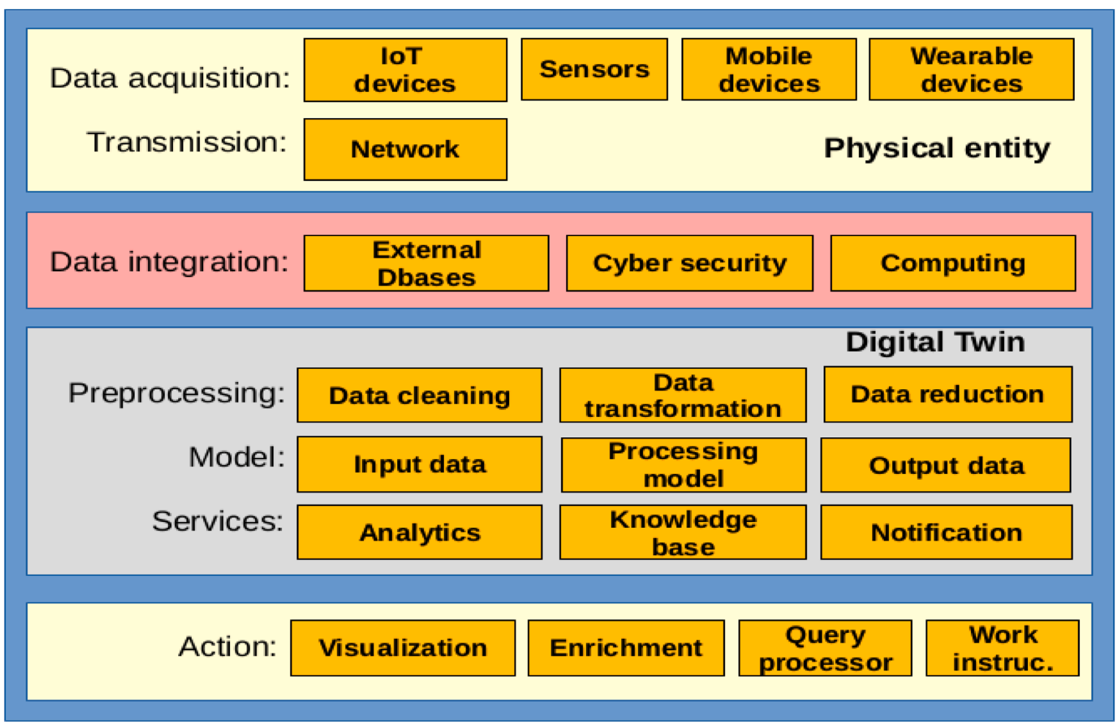

Fig. 2. Architecture of a digital twin.

and sensors, or structured data from external databases in a format understandable by the DT process model. The DT process model is a representation of a physical entity, and, therefore, the model must be able to simulate its operations. This model produces output data similar to the physical entity. There are especially three kinds of services used by a DT process model: (1) analytics, (2) knowledge base, and (3) notification. Analytics refers to predetermined ML models that are often used for forecasting or anomaly detection (Joshi, 2022). Knowledge base addresses those forecasting ML models that reports their output through a set of rules. Notifications take place when the outcome of analytics needs attention and can be communicated using different mechanisms (e.g., e-mail, SMS, etc.).

A DT user is notified about performing a potential action through application interfaces. Typically, the following application interfaces are applied more frequently a by DT: (1) visualization, (2) enrichment, (3) query processor, and (4) work instructions. Visualization is a tool often used for gaining insights into the current status of the particular DT, and thus enables a user to respond to the situation properly. An enrichment changes the way in which the results of the DT model made in the virtual environment interact with the physical world. The query processor application interface allows the DT user to enter a query to the specific data source, and the obtained results are applied in the decision-making process. Work instructions are an application interface capable of instructing the DT user by a description of specific actions, typically, in the sense of the Augmented Reality (AR).

2.1. *Digital twins in sport*

Sport plays an important role in human life. Moreover, modern sport can be treated as a surrogate religion or popular theater, in which people identify themselves with the sport's champions (Fister et al., 2019). On the other hand, the modern sedentary lifestyle, and, consequently, the lack of activity cause obesity and loss of fitness by modern people. The lack of activity hurt them the most in the time of the Corona19 pandemic. The crisis had an especially bad effect on the younger generation. In line with this, the sport can help to improve those harmful influences on the modern lifestyle.

Recently, DT technology has become increasingly significant in the sport domain, where it provides advanced solutions for sport training, performance monitoring, and strategical planning (Miller and Spatz, 2022). Indeed, the DT in sport presents a kind of human DT, where the human (i.e., the athlete) is placed in the center of the scene. Thus, humans are monitored in the physical world by various wearable devices and sensors, while the data acquired from these devices are transmitted to both, i.e., the real athletes and their virtual replicas modeled by the DT. These data are analyzed using the DT process model, while the obtained results are passed to the monitored athlete in the sense of an (AR). The athlete then makes a decision on how to respond to a specific situation during a training session or competition. Interestingly, the DT in sport does not distinguish between the professional and amateur athletes.

3. Research methodology

The goal of this review was to: (1) explore how digital technology is being integrated into sports training to enhance the capabilities of athletes and coaches, and (2) assess the extent to which these technological innovations are being implemented in real-world sports settings. Based on these objectives, the following Research Questions (RQ) were formulated:

- **RQ1**: Which sports are supported the most by DTs? (Section 5)
- **RQ2**: What is the level of maturity and practical implementation of DT technology in sports settings? (Section 6)
- **RQ3**: How do DTs influence sports training? (Section 7)
- **RQ4**: What are the challenges of implementing DTs in sports? (Section 8)

A **Systematic Literature Review (SLR)** was the empirical research method to answer the research questions. The following SLR Guidelines in Software Engineering (Kitchenham and Charters, 2007) were followed to conduct this review by us: We initially scanned the domain by examining the relevant literature from leading digital databases in software engineering, prepared the SLR (conducted from April 15 to April 23, 2024) and developed appropriate search strings. During the initial domain scan, it became clear that actual implementations of DTs in sports are notably rare. There are only a few studies focused specifically on this area within sports. In contrast, most research on human DTs focuses predominantly on healthcare. Additionally, while DTs originate from industrial applications and are utilized extensively in sectors such as logistics and manufacturing (Jiang et al., 2021), their adaptation to human-centric applications outside of healthcare, especially in sports, remains limited.

We formed a search string based on two groups of keywords. Group **one** included the keywords ”digital twin” (variation: ”digital twins”). Group **two** included ”sport” (variation: ”sports”), ”fitness”, ”coaching”, and ”virtual trainer”. Based on the keywords, the single aggregated search string used to perform the SLR was as follows:

(“digital twin”) **AND** (“sport” **OR** “fitness” **OR** **“**coaching” **OR** “virtual trainer”).

Variations in the search strings used across different databases were necessary, due to the distinct query languages and constraints unique to each scientific paper database. The queried databases are shown in Table 1.

Table 1
Databases with search results and total after removing duplicates.

Database Name	URL	Number of papers	
		Total	Included
ACM Digital Library	dl.acm.org	38	0
Google Scholar	scholar.google.com	414	15
IEEE Xplore	ieeexplore.ieee.org	92	1
ScienceDirect	sciencedirect.com	9	0
Scopus	scopus.com	86	5
SpringerLink	link.springer.com	100	3
Total		739	24

The selection and exclusion criteria were defined clearly, and the limitations were considered carefully, to ensure a comprehensive and current understanding of the field.

Thus, the **selection criteria** were as follows:

- The research focused specifically on implementing or applying DT technology in sports for athletes or coaches.
- The research underwent a peer-review process.
- The study pertained to sports as athletic activities demanding skill, physical capability, or competitiveness.
- The research involved using DT technology or related computational methods, such as simulation modeling, artificial intelligence, or realtime data analysis, in the context of sports.

We considered the following **exclusion criteria**:

- The research was not in English.
- The full text of the research was not accessible through the digital library or any subscription services.
- The research focused solely on recognizing activities from a leisure perspective, such as general health.

The limitations of the paper selection were as follows:

- The research was confined to six scientific databases/search engines: ACM Digital Library, Google Scholar, IEEE Xplore, ScienceDirect, Scopus, and SpringerLink.
- The research needed to be published before April 15, 2024, which is when the indexing of potential articles took place.

3.1. Quality assessment

In addition to the selection and exclusion criteria, we performed a quality assessment of the included studies to ensure their relevance and rigor. The quality assessment was based on guidelines as proposed by Kitchenham (Kitchenham and Charters, 2007). The criteria used to evaluate the quality of each study are shown in Table 2.

Each criterion was scored on a scale from 0 to 2, where 0 indicates that the criterion was not addressed, 1 indicates partial fulfillment, and 2 indicates full fulfillment. The total quality score for each study was calculated by summing the scores for each criterion, with a maximum possible score of 12. Indeed, the quality scores were used to ensure that only high-quality studies were included in the final synthesis of the literature.

Table 2
Quality assessment criteria.

Criterion	Description
Research Design	The clarity and appropriateness of the research design, including the study’s objectives and research questions.
Data Collection	The methods used for data collection, ensuring they are appropriate and well-documented.
Data Analysis	The methods used for data analysis, including the validity and reliability of the results.
Bias and Limitations	The identification and management of potential biases and limitations in the study.
Relevance	The relevance of the study to the research questions posed in this review.
Impact	The significance and impact of the study’s findings on the field of DTs in sports.

3.2. Data extraction

Data extraction was performed according to the guidelines as proposed by Kitchenham (Kitchenham and Charters, 2007). The following data items were extracted from each study, as shown in Table 3.

The data extraction was performed independently by two researchers to ensure accuracy and consistency. Any discrepancies were resolved through discussion, and a third researcher was consulted if necessary. The extracted data were then tabulated, and used to synthesize the findings of the included studies.

3.3. SLR Progression

The **SLR Progression** is shown in Fig. 3:

- **Phase 1: Initial search.** In the first phase, we conducted an initial search, which produced **739** results. Out of these, only **493** were available to be read in full-text form. During our preliminary research, we discovered that most works concentrate solely on the health aspect rather than sports, which led us to add an exclusion criterion: research focused exclusively on recognizing activities from a leisure perspective, such as general health.
- **Phase 2: Title-based screening.** In this phase, three researchers reviewed the study titles independently. Their findings were combined to promote a well-rounded and impartial selection process. This step allowed us to pinpoint studies that were appropriate for the next stage of the review (**67** results).
- **Phase 3: Abstract-based screening.** In this phase, the abstracts and keywords of each study were reviewed carefully. The results were then aggregated, to identify studies that met the criteria (**45** results), ensuring a focused selection process for the next review stage.
- **Phase 4: Full-text review.** The full-text review was the subsequent phase of the SLR, yielding an initial set of 32 primary studies. After removing duplicates, we had a final collection of **24** primary studies.
- **Phase 5: Snow-balling.** In the final phase, we used a related work review to identify additional studies through the snowballing technique. However, no new literature was found during this process, so the review remained focused on the **24** primary studies identified in the previous phase.

The field of DTs in sports has been rising in popularity over the last few years, as demonstrated in Fig. 4. The first two identified primary studies were from the year 2019, and this trend continued in the year 2020. Its popularity started increasing sharply in 2021, when 5 identified primary studies were identified. We hit the peak in the year 2022 with 7 identified studies. In the year 2023, there were 5 studies. The data for 2024 are of a different shade and hue, since the year is still in progress, and we anticipate that more research will be published.

The results of the literature search analysis are provided in the remainder of the paper.

Table 3
Data extraction from the selected studies.

Data item	Description
Bibliographic Information	Authors, title, year of publication, source.
Study Context	Description of the study setting, including the sports context and the specific application of DT technology.
Research Methodology	Description of the research methods used, including design, data collection, and data analysis techniques.
Key Findings	Summary of the main findings of the study related to the research questions.
Challenges and Limitations	Identification of any challenges or limitations reported in the study.
Implications	Implications of the findings for practice and future research.

4. Detailed analysis of the DT in sport

The purpose of the analysis was to evidence details of the various DTs that were found in the collection of the papers, and to expose their main characteristics. The results of the investigation are summarized in Table 4 that, in columns, presents information like: (1) the name of the specific DT, (2) the data acquisition methods for exploring the physical world, (3) the DT model for simulating the real entity, and (4) the references to the papers where these were described, according to the particular sports discipline.

The following conclusions can be exposed from Table 4: The crucial differences in DT implementations have been indicated by application in different sports. Thus, the biggest differences arise when comparing the implementations of DTs supporting either individual or team sports. In individual sports, the DTs play the role of training assistant, virtual coach, or even educator. As a training assistant, the DTs try to enhance an athlete's performance and reduce their injury risks. The virtual coach DT simulates the tasks of real coaches, and, thus, tries to replace their role in the training process. Educator DTs replace either the real educators in physical education or teachers of artistic gymnastics. Usually, these application solutions are equipped with IoT devices, RFID tags, and wearable non-invasive sensors (e.g., ANT+sensors). Recently, the DTs have been equipped with video cameras (e.g., DTCoach) and Kinect or motion sensors (e.g., in gymnastics, dancing, and education), where they try to improve the athlete's movement. On the other hand, the DTs, in team sports like football and basketball, serve as real coaches for improving strategic and tactical decisions or monitoring and simulating players' movements and health conditions in real time. Typically, these solutions explore the power of smart insoles and haptic feedback devices (e.g., a smart haptic display).

Different NNs are applied for modelling the physical world. Thus, the shallow NN with only one or two hidden layers and an LSTM for dealing with data based on time series were discovered during the analysis. The primary characteristic of these NNs is the time complexity, and, consequently, these are not the most appropriate for use in real-time applications. Therefore, the more appropriate models are based on real-time analysis, MC simulation, and Hidden MM. Some models were developed especially for particular sports disciplines, for instance, motion sequence generation in gymnastics or Newton's laws of motion in swimming.

4.1. Performance improvements and qualitative insights

As mentioned, in our comprehensive literature review, we identified and analyzed various DT concepts, proposals, and implementations in sports.

These DTs, whether fully realized or still in the conceptual stage, are categorized based on three key measures (Table 5): **performance improvements**, **athlete feedback**, and **coach satisfaction**. Thus, the performance improvements refer to measurable enhancements in athletes' abilities or results due to training, technology, or other interventions. These improvements can be quantified using metrics such as increased speed, strength, endurance, accuracy, agility, power, and other sport-specific skills. Athlete feedback involves the qualitative information athletes provide regarding their experiences, perceptions, and responses to training programs, coaching methods, and technological interventions. This feedback is essential for tailoring and optimizing training regimens to meet individual needs. Coach satisfaction represents the degree of contentment and approval expressed by coaches regarding the effectiveness of training programs, the performance of athletes, and the outcomes of using specific technologies or methodologies in their coaching practices. These categories illustrate both the measurable outcomes and experiential insights that reflect the potential and actual impact of DT technologies. It is important to note that some of the identified DTs are still in the early stages of development and are not yet applicable to specific areas.

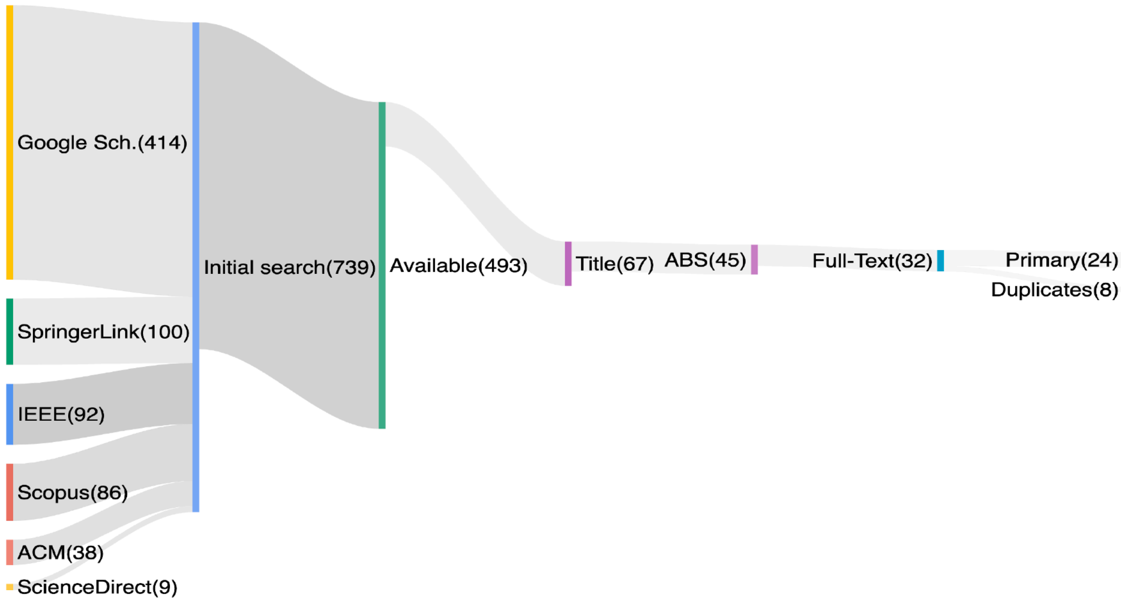

Fig. 3. SLR progression.

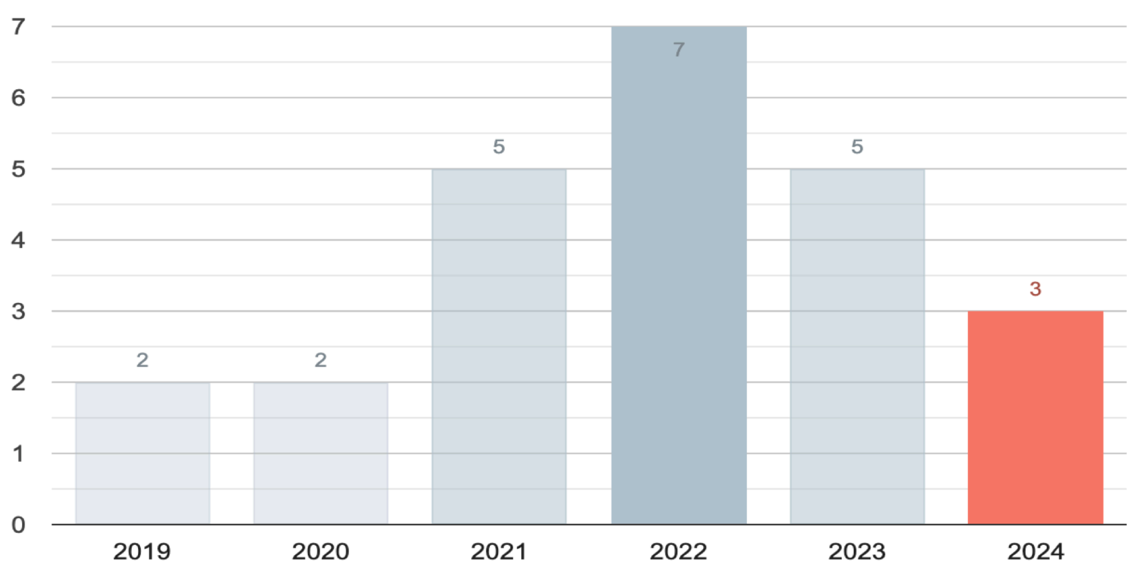

Fig. 4. Year-wise histogram of papers on digital twins in sports.

4.2. *Strengths and limitations of DTs in sports*

By creating virtual replicas of athletes, DTs enable detailed monitoring, personalized feedback, and data-driven decision-making. However, the implementation of DTs also presents various challenges. Based on a comprehensive review of primary literature, the following sections outline the general strengths and limitations of DTs in sports (Table 6).

In the remainder of the paper, the exposed strengths and limitations are discussed in detail.

4.2.1. *Strengths*

Enhanced performance analysis: DTs offer detailed insights into an athlete's performance by collecting and analyzing data from various sensors (Chen et al., 2022; Lloyd et al., 2023). For example, the DTCoach system uses cameras and shallow neural networks to provide real-time feedback on exercise performance, enabling immediate adjustments to improve efficiency and effectiveness (Ǵamez Dıaz, 2021). This real-time feedback can be critical for athletes to make the necessary adjustments during training sessions, leading to improved performance outcomes. Additionally, integrating neuro-feedback techniques, as highlighted by Cheng et al. (Cheng et al., 2024); emphasizes the connection between DT technology and advancements in sports medicine. EEG neuro-feedback training helps athletes optimize their mental states, complementing the physical training data collected by the DTs. This holistic approach, combining physical performance metrics with cognitive training, can lead to significant enhancements in athletic abilities (Cheng et al., 2024). Moreover, one of the significant advantages of using DTs is their ability to uncover relationships and dependencies that are not immediately apparent to coaches. By applying advanced DM techniques, such as those discussed by Fister et al. (Fister et al., 2019), DTs can reveal intricate patterns and correlations within the training data. These insights can inform coaches about subtle factors affecting performance, which may not be visible through traditional observation alone. For instance, analyzing complex networks and association rules can

Table 4
Detailed analysis of the DT in sport.

Sport	Name	Data acquisition	DT model	Papers
Fitness & Health	DT Coaching	Video cameras	OpenPose	(Chen et al., 2022 (ICAEIC-2022) (2022).)
	DTCoach	Cameras	Shallow NN	(Ďiaz et al., 2021; Ǵamez Ďıaz et al., 2020; Ǵamez Ďıaz, 2021)
	Digital Athlete	Depth Cameras	NMSK, LSTM	(Lloyd et al., 2023)
	SmartFit	IoT devices	ECOC	(Barricelli et al., 2020)
	DT for Fitness	IoT devices	MLSTM	(Alsubai et al., 2023)
Cycling	AST Monitor	ANT+sensors	Real-time analysis	(Fister et al., 2021; Lukač, Fister, & Fister, 2022; Fister et al., 2021)
	DT Model	Cycling ergometer, instrumented pedals	Margaria-Morton model	(Boillet et al., 2024)
Football	Conn. Footballer	Chest strap, RFID tag	MC Simulation Algorithm	(Balachandar et al., 2019)
	Athlete Training Sys.	Smart insoles	Probabilistic Model	(Laamarti, 2019)
	Aid Robots DT	Lidar, Camera	Dec-POMDP	(Pham et al., 2023)
	Turtle DT	Cameras	Real-Time Database	(Walravens et al., 2022)
Shooting	Shooting DT	Wearable sensors, motion capture, physiological sensors	Decision Tree Algorithm	(Morzenti, 2023)
Education	DT in education	Kinect sensors	Hidden Markov Model	(Liu and Jiang, 2022)
Dancing	MetaHuman	Dance motion capture	OpenSim	(Cedermalm and Sars, 2022)
Swimming	DT for swimmers	IMU, Force sensor	Newton's laws of motion	(Douglass et al., 2024)
Gymnastics	DT for Gymnastics	VR image recognition, motion sensors	Motion sequence generation motion editing algorithm	(Shi, 2021)

highlight specific training conditions or combinations of exercises that lead to optimal performance improvements, thereby providing a deeper understanding of the athlete's development.

Personalized training programs: By leveraging data from IoT devices and ML methods, DTs can create customized training programs that adapt to the athlete's progress. For instance, SmartFit utilizes a comprehensive fitness management system that offers personalized fitness plans based on real-time data analysis (Barricelli et al., 2020; Alsubai et al., 2023). Moreover, generating weekly training plans for swimmers using genetic algorithms and random trees demonstrates how DTs can provide tailored training schedules. This method not only matches the training style of professional coaches but also adapts to the specific needs and progress of individual swimmers, ensuring that each athlete receives a personalized and effective training program (Eriksson et al., 2021). Similarly, the case-based reasoning system developed for marathon runners offers personalized training recommendations based on their training histories and the practices of similar runners. This system, which uses data from wearable devices like smartwatches, provides incremental training adjustments to help runners achieve their fitness goals, ensuring that training programs are both realistic and personalized (Feely et al., 2023).

Table 5
Performance improvements and qualitative insights influenced by DTs in sport.

Sport	Name	Performance improvements	Athlete Feedback	Coach Satisfaction
Fitness Health	DT Coaching			
	DTCoach	✓	✓	✓
	Digital Athlete	✓		
	SmartFit	✓	✓	
	DT for Fitness			
Cycling	AST Monitor		✓	
	DT Model	✓		✓
	Conn. Footballer			
Football	Athlete Training Sys.			
	Aid Robots DT	✓		
	Turtle DT	✓		
Shooting	Shooting DT			
Education	DT in Education			
Dancing	MetaHuman			
Swimming	DT for Swimmers	✓		
Gymnastics	DT for Gymnastics			

Table 6
General strengths and limitations of DTs in sports.

Strengths	Limitations
- Enhanced performance analysis	- Technical complexity and maintenance
- Personalized training programs	- Dependence on accurate and high-quality data
- Injury prevention and management	- Data privacy and security concerns
- Enhanced coaching capabilities	- Limited accessibility and inclusivity
- Improved engagement and motivation	- High implementation costs

Injury prevention and management: DTs can identify potential injury risks by analyzing biomechanical and physiological data, allowing for preventive measures to be taken. As an example, the Digital Athlete model, initially designed for soldiers, uses depth cameras and LSTM models to monitor musculoskeletal health, reducing injury risks during training (Lloyd et al., 2023; Fister et al., 2021).

Enhanced coaching capabilities: DTs enable remote coaching, and provide comprehensive data that coaches can use to tailor strategies and techniques. The Connected Footballer DT, for instance, integrates smart insoles and RFID tags to help coaches analyze player performance and adjust training programs accordingly (Ǵamez Ďıaz, 2021; Pham et al., 2023; Balachandar et al., 2019).

Improved engagement and motivation: By incorporating gamification elements and providing real-time feedback, DTs can enhance athlete motivation and engagement. For example, the DT for Gymnastics uses VR image recognition to create an interactive training environment that keeps athletes engaged (Shi, 2021; Laamarti, 2019).

4.2.2. *Limitations*

Technical complexity and maintenance: DTs require continuous technical support and maintenance to function properly. The DTCoach system, for example, needs regular updates and technical oversight to ensure its accuracy and effectiveness (Ǵamez Ďıaz, 2021; Walravens et al., 2022).

Dependence on accurate and high-quality data: The effectiveness of DTs is highly dependent on the quality and accuracy of the collected data (Douglass et al., 2024). Therefore, Chen et al. (Chen et al., 2022) emphasized that any errors or inconsistencies in data can lead to incorrect feedback and recommendations.

Data privacy and security concerns: The collection and analysis of sensitive athlete data pose privacy and security risks (Laamarti, 2019). In line with this, Alsubai et al. (Alsubai et al., 2023) discussed the importance of ensuring data privacy and the potential consequences of data breaches.

Limited accessibility and inclusivity: High-tech solutions like DTs may not be accessible to all athletes, especially those in less developed regions (Laamarti, 2019). Consequently, Liu et al. (Liu and Jiang, 2022) noted that the DT systems used in physical education require significant infrastructure, which may not be available everywhere.

High implementation costs: Implementing DTs requires significant investment in sensors, devices, and software, which can be a barrier for widespread adoption (Shi, 2021). As an example, Boillet et al. (Boillet et al., 2024) highlighted the high costs of developing and maintaining individualized DT models for sports performance prediction.

5. Issue 1: Taxonomy of the digital twin in sport

This section introduces a taxonomy of DTs in sports, by categorizing the various types, applications, and traits of DTs, to provide a comprehensive overview of how DT technology is utilized across different sports disciplines. The characteristics of various kinds of DTs were, theoretically, well elaborated (Patel et al., 2022). Therefore, the taxonomy of DT in sport follows these hints. Indeed, the classification of DTs can be performed by considering more aspects, such as, for instance:

- types of DTs,
- applications of DTs,
- traits of DTs.

In the remainder of the paper, the exposed aspects are discussed in more detail.

5.1. Types of digital twins

Grieves, one of the pioneers of DT development, in his early study from 2015 (Grieves, 2014); established that a DT consists of three components, as follows:

(1) a physical product, (2) a virtual representation of the product, and (3) the bi-directional data connection from replicas of the physical entity to a virtual representation, as well as information and processes from the virtual representation, to a replica of the physical entity. These components form the so-called product life-cycle that can also be applied to DT development. Later, Grieves in (Michael, 2017) defined three types of DTs entering into the product life-cycle, as follows:

- Digital Twin Prototype (DTP): A *prototype* that served as the initial model for the DT, often used in the design and development phase (i.e., system shape of the DTP in the virtual world only).
- Digital Twin Instance (DTI): An *instance* representing a specific, individual unit of equipment or system in operation that connects the virtual and physical worlds.
- Digital Twin Environment (DTE): An *aggregate of multiple DTIs or DTPs* used for analyzing trends and performance across a fleet or system. The DTEs are categorized based on their functionality, as:
  - Predictive: These DTs forecast future behaviors and performances using historical and real-time data, aiding in preemptive decisionmaking and strategy development.
  - Interrogative: These systems focus on displaying the current and past states of the physical system, enabling users to query and understand historical performance and operational metrics.

Actually, a DT model goes through three phases during its life-cycle (Michael, 2017): At the beginning, it emerges virtually as a prototype, then, continues through its operational life, and, finally, it is eventually retired and disposed of.

5.2. Applications of digital twins

The area of DT applications depends on the level of product magnification. Thus, different types of DT applications can co-exist within a system or process. In general, regarding the type of applications, DTs can be classified as follows (Patel et al., 2022):

- Component: A digital model of individual components or parts within a larger system.
- Product: A digital model of entire products or assets capable of simulating their behavior in different conditions.
- System: A digital model of entire systems, offering insights into complex interactions.
- Process: A digital model of entire business processes used often used in manufacturing or operational contexts.

As can be seen from the classification, the area of application can lead to big differences in the implementation of the system.

5.3. Traits of digital twins

Traits of DTs refer to how similar/different are the characteristics of the implemented virtual replica when comparing it with the physical entity. The following traits of DT are found, as follows:

- Same look as the original entity: The DT's look is the same as that of the original entity.
- Different details of the original entity: The DT has the look augmented with different details of the original object, with which they supplement the total look of the effective replica.
- The same behavior as the original entity: This trait enables a DT to behave and look the same as the original entity.
- Prediction and information about problems that could arise in advance: DTs with these traits are able to predict the problems that could occur in the future, and, consequently, try to avoid them.

In general, human DTs in sport do not have the same look as the original ones, but operate with different details of the original. In other words, these DTs operate with the physical information that determines the particular human in the real-world, and, thus, mimic their behavior.

5.4. Summary

The proposed taxonomy of the DTs in sport classifies the collection of elaborated papers according to three aspects, as follows: (1) types, (2) applications, and (3) traits of the DT. The results of the investigation are illustrated in Table 7, that is organized as a 3D cube, where the different DT aspects are represented on the X-axis, the names of the DTs on the Y-axis, and attributes of the aspects on the Z-axis. Interestingly, the number of papers, in which the definite DT is mentioned, has been added to the "Type" aspect.

As can be seen in Table 7, the majority of the DTs are described by only one paper. This could be evidence of a fact that these DTs are either in the prototype phase, or have already come out of development phase, and, therefore, need additional experimental work to get proper scalability and efficiency for using in practice. The exceptions are AST Monitor and DTCoach that are introduced in three papers, which illustrate the development of both from the DTP to DTE.

The area of applications for the different DTs in the Table started from the component via product to system. While the AST Monitor is a part of the universal big system Artificial Sport Trainer (AST) (Fister

Table 7
Taxonomy of the digital twin in sport.

Digital Twin	Type: Nr. of papers	Type: DTP	Type: DTI	Type: Predictive DTE	Application: Component	Application: Product	Application: System	Application: Process	Trait: Same look	Trait: Different details	Trait: Same behavior	Trait: Prediction & information
Aid Robots DT	1	●	●	●	▲					■		■
Athlete Training Sys.	1	●	●	●			▲			■		■
AST Monitor	3	●	●	●			▲			■		■
Conn. Footballer	1	●			▲					■		
Digital Athlete	1	●	●	●		▲				■		■
DT for Fitness	1	●	●	●		▲				■		■
DT for Gymnastics	1	●	●	●	▲					■		■
DT for swimmers	1	●	●	●	▲					■		■
DT in education	1	●	●	●	▲					■		■
DT Model	1	●	●	●	▲					■		■
DTCoach	3	●	●	●			▲			■		■
DT Coaching	1	●	●	●		▲				■		■
MetaHuman	1	●	●	●		▲				■		■
Shooting DT	1	●			▲					■		
SmartFit	1	●	●	●		▲				■		■
Turtle DT	1	●			▲					■		

et al., 2021), the DTCoach bases on the pre-trained light pose estimation model capable of feedback generation using a mobile device, and can be applied for many fitness, health and well-being purposes. On the other hand, the Athlete Training System consists of more different DTEs that can be applied in the same application areas supported by DTCoach. The majority of the remaining proposed DTs emerged as components that are devoted to train only a particular training area in a specific sport discipline. For instance, the shooting DT (Morzenti, 2023) focuses on monitoring the shooter's pose by measuring kinematics and physiological sensors. Thus, the shooter is only one of the components during this training session. Well-represented are also DTs covering the product application area. Digital Athlete (Lloyd et al., 2023), for example, concentrates itself on maintaining a soldier's muscolo-skeletal health with wearable sensors and computer vision, and, thus, represents the complete solution of this military area.

The majority of the analyzed DTs have a look with different details of the original human, but all except DTPs are able to make predictions about problems that could arise in advance.

6. Issue 2: Real examples of digital twins

This section provides real-world examples of DTs in sports, addressing **RQ2** by examining the practical implementation and maturity of DT systems. DTs are revolutionizing sports by enhancing training and performance analysis with advanced data-driven insights. This technology now provides athletes and coaches with precise simulations and real-time feedback, fundamentally transforming athletic preparation and strategy.

The aim of the study was to analyze two of the more complete real-world solutions within the DT system, as follows:

- AST Monitor,
- DTCoach.

Both real-world implementations cover an area of sport training, but in different sport disciplines, i.e., cycling and fitness. Their completeness is also evident by more papers being published that highlight these DT systems from various aspects.

In the remainder of the section, the mentioned real-world implementations are explored across various sports disciplines in more detail. The section is finished with an analysis of the key factors for estimating the quality of DT implementation.

6.1. AST Monitor

AST monitor (Fig. 5) is a part of the universal AST system (Fister et al., 2021) dedicated for monitoring an athlete during the cycling training session. A specification of the training session is obtained from the AST system in the form of a Domain-Specific Language (DSL). The DT advises the cyclist during the training session with personalized guidance in the form of an AR via display connected to Raspberry Pi microcomputer, which is mounted on the cycle. A powerbank is used as a source of electrical energy. A DT model is implemented as a feedback system based on the simple mathematical model for prediction of the Heart Rate (HR), necessary to satisfy the requirements of the training session by the cyclist. Among other features, the AST Monitor is equipped with a variety of ANT+sensors connected to the Raspberry Pi, like HR, power meter, and speed sensor, as well as a GPS receiver and a WiFi transmitter. The Raspberry Pi enable mobility, scalability, security, and connectivity, and, therefore, represents a promising platform for development of DTs in the future.

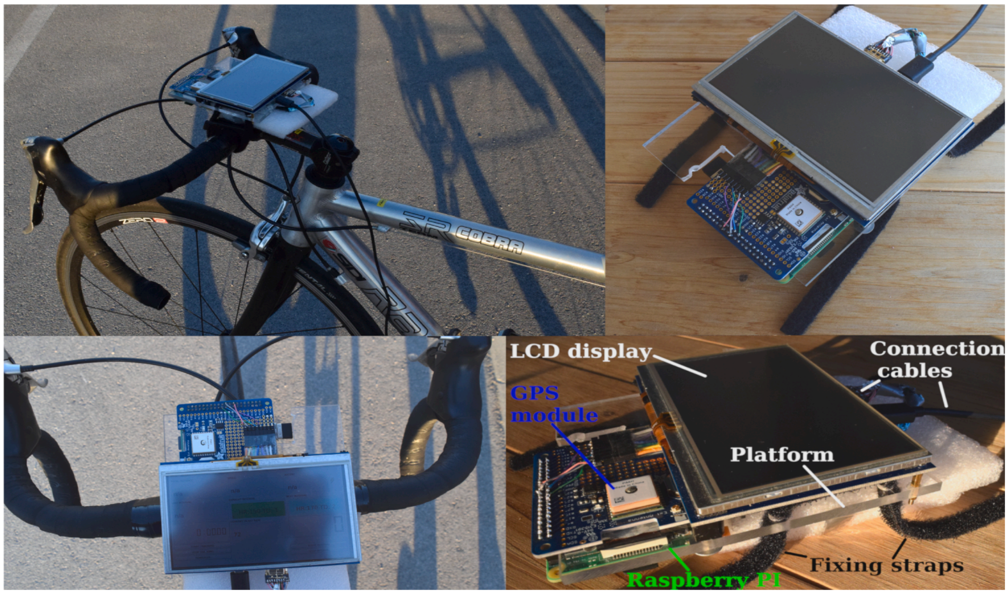

Fig. 5. AST Monitor[1]. [1]Fister, Jr., I., & Fister, D. (2024). firefly-cpp/figures: 1.0 (1.0). Zenodo. https://doi.org/10.5281/zenodo.10479320.

6.2. DTCoach

In the study from Diaz (Díaz et al., 2021), a DTI is developed for real-time physical activity coaching on mobile devices, highlighting an interrogative DTE that provides immediate feedback based on user performance. This system utilizes edge computing to enable a portable and accessible coaching product that operates effectively on users' smartphones. The DT features advanced ML algorithms, including lightweight neural networks for pose estimation, tailored to run efficiently on devices with limited processing power. This capability ensures that users receive personalized training guidance directly from their mobile devices without the need for complex sensors or additional hardware. The system's main advantages include its ability to offer real-time, personalized feedback, enhancing the effectiveness of home-based physical training significantly. Implementing this technology posed several challenges, particularly in optimizing data processing to function within the constraints of mobile technology. The solution employed pre-processing techniques to reduce computational demands, and ensure the system's responsiveness. Additionally, the development team faced challenges related to ensuring data security and user privacy, critical when handling sensitive health data on mobile platforms. This DT application not only supports individualized fitness goals, but also adapts to each user's unique physical conditions, providing a scalable solution that enhances physical activity through advanced technological integration (Díaz et al., 2021).

6.3. Other DTs in sports

In addition to AST Monitor and DTCoach, several other DTs have been developed or are in the proposal phase, to enhance various aspects of sports. Although these DTs are not documented in the literature as extensively as AST Monitor and DTCoach, they are, nonetheless noteworthy for their unique contributions and potential. This section describes these diverse implementations briefly, showcasing the wide-ranging impact of DT technology in the sports domain.

The *Digital Athlete* model focuses on maintaining musculoskeletal health, designed initially for soldiers, but applicable to athletic training. By integrating wearable sensors and computer vision, this DT provides personalized health monitoring and feedback based on real-time data, aiming to enhance training efficiency and reduce injury risks (Lloyd et al., 2023).

In general fitness, *SmartFit* emerges as a comprehensive fitness management tool. This DT integrates data from various IoT devices, to offer enhanced data analytics, personalized fitness plans, and real-time monitoring. The goal is to optimize fitness routines and support users in achieving their health objectives through precise and tailored feedback (Barricelli et al., 2020).

Fitness management is enhanced further by the *DT for Fitness*, which integrates data from wearable devices and manual inputs to provide continuous and dynamic representations of athletes' health and fitness. This DT employs ML methods for data analysis, performance prediction, and personalized feedback, ensuring a comprehensive approach to fitness management (Alsubai et al., 2023).

Football sees significant advancements with the proposal of *Connected Footballer* DT, designed to improve strategic and tactical decision-making. Utilizing smart insoles, RFID tags, and ML methods, this DT design enables real-time data analysis, helping coaches and players adjust strategies and enhance performance during games (Balachandar et al., 2019).

The *DT Model* for sports performance prediction reinterprets the Margaria-Morton model to create individualized DTs. This DT uses physiological data to predict and optimize performance, offering a tailored approach to athlete training and competition strategies (Boillet et al., 2024).

The *Athlete Training System* is a comprehensive training tool incorporating various DT elements. This DT utilizes smart insoles and probabilistic models to enhance training and performance, providing detailed insights and recommendations for athletes (Laamarti, 2019).

Aid robots in soccer are improved through the *Aid Robots DT*, which focuses on multi-agent decision-making and training. By employing Lidar, cameras, and Decentralized Partially Observable Markov Decision Processes (Dec-POMDP), this DT enhances strategic decision-making and training efficiency in robotic soccer (Pham et al., 2023).

Similarly, the *Turtle DT* for soccer robots leverages pre-existing software artifacts to build a digital shadow. This DT uses CAD models and a virtual environment to simulate soccer robots, enabling efficient strategy development and performance optimization (Walravens et al., 2022).

Precision sports benefit from the *Shooting DT*, which focuses on enhancing shooting accuracy and technique. This DT proposal integrates wearable sensors and motion capture technology to provide real-time feedback and performance analytics, supporting athletes in refining their skills with detailed insights (Morzenti, 2023).

In the educational sector, the *DT in Education* improves physical education teaching practices and student performance. By employing Kinect sensors and Hidden Markov Models, this DT provides interactive and personalized educational experiences, making learning more engaging and effective (Liu and Jiang, 2022).

Artistic disciplines are not left behind, as the *MetaHuman* DT simulates and analyzes dance movements and artistic gymnastics. Using motion capture and biomechanical modeling, this DT helps performers optimize their techniques, ensuring precision and grace in their movements (Cedermalm and Sars, 2022).

For swimmers, the *DT for Swimmers* offers a comprehensive analysis of underwater movements. Utilizing IMUs and force sensors, this DT monitors and optimizes swimming techniques such as streamline and dolphin kick, helping athletes achieve better efficiency and speed in the water (Douglass et al., 2024).

Gymnastics training has been revolutionized by the *DT for Gymnastics*, which leverages VR image recognition and motion sensors. This DT provides detailed feedback and motion sequence generation, aiding gymnasts in perfecting their routines and enhancing overall performance (Shi, 2021).

Finally, *DT Coaching* addresses the gap in autonomous fitness by using OpenPose to create a dataset called HumanFIT AI. This DT evaluates and gives feedback on fitness postures, ensuring effective exercises and reducing injury risks through detailed real-time feedback (Chen et al., 2022).

These diverse applications demonstrate the potential of DTs in sports. DTs enhance athletic performance, training efficiency, and overall management in the sports domain significantly by providing tailored solutions for individual and team sports.

6.4. Key factors for estimating the quality of digital Twin implementations

The key factors that define the capabilities and benefits of DTs were estimated according to the following aspects:

- Capability: What the DT is technically capable of doing?
- Advantages: The specific benefits provided by the DT, such as increased efficiency or reduced downtime.
- Features: Distinctive attributes or functions of the DT system.

The results of analyzing the key factors for estimating the quality of DT implementation of AST Monitor and DTCoach can be observed in Table 8, from which it can be indicated that users of the former interact with the DT model using Raspberry Pi, while users of the latter use mobile devices.

7. Issue 3: How do digital twins shape the world of current and future sports?

This section discusses the impact of DTs on sports training and strategy, addressing **RQ3** by illustrating how DTs provide real-time feedback, personalized training programs, and advanced performance analysis.

DTs offer new potential in sports by creating virtual replicas of athletes in their environments. Our extensive literature review discovered some areas that need to be exposed. For example, these DT replicas can be applied in the following sport domains:

- performance analysis and enhanced training,
- injury prevention and recovery,
- strategic planning and competition simulation.

The results of the investigation study are summarized in Table 9, that illustrates the key benefits of DTs in sport, which could change the current and future sport radically. In the remainder of the paper, the key benefits of DTs in sports are dealt with in detail.

7.1. Performance analysis and enhanced training

DTs integrate data from various sensors (e.g., IoT devices, wearable sensors) to monitor biometrics such as heart rate, oxygen levels, and muscle activity (Ǵamez Ḋıaz, Yu, Ding, Laamarti, & El Saddik, 2020; Lukač, Fister, & Fister, 2022; Laamarti, 2019). These data allows highly personalized training programs that adapt to the athlete's needs and conditions in real-time (Balachandar et al., 2019; Morzenti, 2023).

The development of smart training systems gives us advanced simulations that help correct technical errors and optimize movements. For instance, DTs in cycling can simulate interval training scenarios, to advise the best strategies for improving efficiency and performance (Lukač, Fister, & Fister, 2022).

Another example presents sports like swimming, where DTs analyze underwater movements, in order to optimize techniques, such as streamline and dolphin kick, leading to significant performance gains (Douglass et al., 2024).

One key aspect of training is psychological and motivational support, achieved by visualizing progress, setting realistic goals, and providing con– tinuous feedback. This helps maintain an athlete's motivation and adherence to training programs. On the other hand, they can simulate the psychological impact of different training and competition scenarios, helping athletes prepare mentally for high-stress situations (Morzenti, 2023; Sahal et al., 2022; Barricelli et al., 2020; Fister et al., 2021).

7.2. Injury prevention and recovery

As many authors have stated, DTs enable detailed analysis of an athlete's biomechanics, help to identify potential injury risks, and correct his/her wrong techniques. For example, the use of sensors to capture detailed motion data and assess techniques, can pinpoint areas that need improvement and prevent injuries (Ǵamez Ḋıaz et al., 2020; Lloyd et al., 2023; Laamarti, 2019).

On the other hand, rehabilitation is an important aspect that needs to be covered. DTs assist rehabilitation by monitoring recovery progress

Table 8
Estimation of the quality of real-world DT implementations.

Key factor	AST Monitor	DTCoach
Capability	Personalized training guidance from RaspBerry Pi	Personalized training guidance from a mobile device
Advantages	Real-time AR feedback	Real-time personalized feedback
Features	Lightweight prediction algor., Variety ANT+sensors, Raspberry Pi	Lightweight NN, Limited processing power

Table 9
Key benefits of digital twins in sports.

Domain	Key benefits	Papers
Performance analysisand enhanced training	Personalized training, real-time adaptations	(Balachandar & Chinnaiyan, 2019; Barricelli, Casiraghi, Gliozzo, Petrini, & Valtolina, 2020; Fister et al., 2021; Ǵamez Ḋıaz, Yu, Ding, Laamarti, & El Saddik, 2020; Lukač, Fister, & Fister, 2022; Laamarti, 2019; Morzenti, 2023; Douglass et al., 2024; Sahal et al., 2022)
Injury prevention and recovery	Biomechanical analysis, real-time recovery monitoring	(Ǵamez Ḋıaz et al., 2020; Lloyd et al., 2023; Laamarti, 2019; Lauer-Schmaltz et al., 2402)
Strategy planning and competition simulation	Data-driven insights, real-time decision-making	(Pham et al., 2023; Walravens et al., 2022)

and adjusting training loads accordingly. They can simulate recovery processes and design optimal rehabilitation protocols to ensure athletes return to their peak performance safely (Laamarti, 2019; Ǵamez D́ıaz et al., 2020; Lauer-Schmaltz et al., 2024; Lloyd et al., 2023).

7.3. Strategy planning and competition simulation

DTs enable athletes and coaches to simulate various competition scenarios and strategies, especially in team sports, providing a powerful tool for optimizing performance. By creating virtual replicas of different game situations, DTs offer data-driven insights that help understand the best performance-enhancing approaches. This detailed simulation allows coaches of teams to make informed decisions regarding the strategy and tactics of the ongoing games. In line with this, the coaches can find the proper position for the player in the game, and, thus, they can ensure that every player's move is planned strategically and executed based on thorough analysis (Walravens et al., 2022).

Moreover, DTs also play a crucial role in real-time decision-making in team sports like football. They simulate game scenarios as they unfold, allowing coaches to adjust strategically during matches. These real-time simulations are driven by predictive analytics, which analyze ongoing gameplay to forecast potential outcomes and suggest optimal strategies. This capability ensures that coaches can respond swiftly to changing conditions on the field, making decisions that can impact the game's outcome significantly. By leveraging the power of DTs, teams can enhance their tactical understanding, and stay ahead in competitive sports environments (Pham et al., 2023).

8. Issue 4: Challenges and opportunities for future development

This section identifies and discusses the challenges associated with implementing DT technology in sports, addressing **RQ4** by highlighting technical, expertise, and data security issues.

Advantages in DT technology have connected seamlessly with growing challenges in areas like AI and IoT. Indeed, implementing DTs involves the following challenges that need to be addressed:

- technical and setup challenges,
- expertise requirements,
- data security and privacy.

Technical and setup challenges include data acquisition, sensor setup, and creating a seamless link between the real and virtual worlds. Fault tolerance in sensors is crucial for maintaining accuracy. Expertise requirements refer to the proper operation of DTs, that require specialized knowledge and skills in both the technology and application domains. Ensuring the security and privacy of data used and generated by DTs is paramount, given the sensitive nature of the data involved. In the remainder of the section, the mentioned challenges are discussed in more detail.

8.1. Technical and setup challenges

The first challenge refers to the following issues:

- interoperability and standardization,
- data acquisition and sensor setup,
- scalability,
- user-friendly interfaces.

Ensuring interoperability and standardization is crucial for the effective implementation of DTs. Adopting standards like ISO/IEEE 11073 (X73) for personal health devices and MPEG-V for sensory devices facilitates seamless integration and data exchange, allowing various systems to work together without dealing with numerous proprietary data formats (Laamarti, 2019). This interoperability is vital for achieving plug-and-play functionality, particularly in Digital Twin Coaching (DTC) systems, where standardized communication protocols enhance overall system effectiveness (Ǵamez D́ıaz et al., 2020). Standardized protocols like IEEE X73 also improve the reliability and robustness of Human Digital Twins (HDTs), ensuring seamless interaction and data exchange (Lauer-Schmaltz et al., 2024).

Data acquisition and sensor setup are critical for DTs. Advanced sensors like 3D accelerometers and bio-sensors capture physiological data accurately, while IoT devices, including smart wearables and RFIDs, gather comprehensive health and environmental data. Proper placement and synchronization of these sensors ensure reliable data capture and real-time communication (Alsubai et al., 2023).

Handling numerous Personalized Digital Twins (PDTs) requires significant resources, due to the complex interactions and frequent updates needed to reflect physical changes. Managing large data volumes and multiple participants is critical for success in broader applications (Sahal et al., 2022).

Creating user-friendly interfaces is crucial for the effective use of DT systems. Simple and intuitive interfaces reduce the expert knowledge required significantly, making the technology more accessible to a wider audience. Incorporating features like clear visual feedback and compatibility with various devices enhances user interaction and engagement. Additionally, using avatars and virtual assistants can improve the user's understanding and trust in the system (Lauer-Schmaltz et al., 2024).

8.2. Expertise requirements

Expertise requirement challenges address primarily the issue of multidisciplinary collaboration. Successful implementation of Human Digital Twin Systems (HDTS) requires robust models addressing various human aspects, including physical, physiological, cognitive, and behavioral factors. This development necessitates a concerted, multidisciplinary effort, to synthesize these models into comprehensive HDTS applications. Such collaboration integrates expertise from different fields, to accelerate the deployment and effectiveness of (Miller and Spatz, 2022).

8.3. Data security and privacy

Data security and privacy direct to the following issues:

- data integrity and security,
- compliance with regulations,
- ethical data management.

DTs involve extensive data collection and processing, raising significant security concerns. Ensuring robust data security through advanced encryption methods and secure storage solutions is critical. Implementing SSL/TLS protocols for data transmission can help prevent breaches and unauthorized access (Ghatti et al., 2023).

Implementing DTs involves strict measures to ensure data security and privacy, focusing on data integrity and security, regulatory compliance, and ethical data management. Additionally, DTs involve extensive data collection and processing, raising significant security concerns. Ensuring robust data security through advanced encryption methods and secure storage solutions is critical. Implementing end-to-end encryption and utilizing secure data storage solutions can prevent unauthorized access and data breaches. Data integrity is maintained through checksums and cryptographic hashes, to verify that data have not been altered during transmission or storage. These measures are equally applicable and critical in DTs in sports, where athlete data must be protected from unauthorized access and tampering (Ghatti et al., 2023; Bruynseels et al., 2018).

Adhering to regulatory Standards like the General Data Protection Regulation (GDPR) is essential for lawful data handling and maintaining user trust. GDPR mandates strict guidelines on data protection, including the rights to access, rectify, and erase personal data. Compliance with these regulations ensures that DT implementations are ethical and legally sound, enhancing their credibility and trustworthiness (Llp, 2023).

Ethical data management requires transparency and user consent, ensuring that athletes are fully informed about what data are being collected, how they will be used, and who will have access. Obtaining informed consent is crucial for ethical compliance. Athletes should be allowed to withdraw their consent at any time, ensuring they retain control over their data. Regular audits and updates on data usage policies are necessary to maintain transparency and trust (Lauer-Schmaltz et al., 2024; Braun, 2022; Mittelstadt, 2021).

Privacy concerns are paramount when dealing with sensitive data in DTs. Data misuse, breaches, and unauthorized access risk highlights the need for stringent privacy protections. Techniques like Blockchain can enhance data security by providing transparent and tamper-proof records of data transactions. Blockchain technology, for instance, can secure athlete health information and training data, optimizing decision-making on resource deployments. Its transparency and security features make it a valuable tool for protecting sensitive data in applications (Ghatti et al., 2023).

AI can bolster the security of DTs further. For example, a Code Bidi rectional Encoder Representation from the Transformers (CodeBERT) based neural network model can analyze written source code to identify and remove security vulnerabilities. Additionally, deep neural networks can recognize search keywords that might compromise data security, and convolutional neural network-based frameworks can differentiate between authentic and spoofed biometric authentication samples, protecting against unauthorized access (Ghatti et al., 2023).

Recent developments in privacy-preserving frameworks aim to enhance data security in DT-based services. One such framework, Privacy-preserving Similarity Query Scheme for Digital Twin-based Healthcare services (PSim-DTH), uses matrix encryption and partition-based indexing to ensure data privacy when external vendors query healthcare data. This approach allows healthcare providers to maintain patient data privacy while enabling authorized access. Similarly, such frameworks can be adapted to protect athlete data in DT applications in sports (Ghatti et al., 2023).

Ethical concerns arise when creating DTs of physical entities, especially if those entities are human beings. Privacy is a significant concern, but there are also worries about exacerbating societal divisions and potential discrimination based on data points. DT studies must be evaluated carefully to avoid discrimination and ensure ethical use. These concerns are pertinent in sports applications, where athlete data must be managed ethically to prevent misuse and discrimination (Llp, 2023; Braun, 2022; Bruynseels et al., 2018).

By addressing these issues comprehensively, DT technologies can be implemented in a manner that is both secure and ethically responsible, thus fostering trust and acceptance among stakeholders and users.

8.4. Opportunities for future development

The future development of DTs presents numerous opportunities across various domains:

- integration with advanced technologies,
- enhanced data analytics,
- advanced sensor technologies.

Advanced technologies, such as AI and ML, can enhance the capabilities of DTs in sports significantly. These technologies enable predictive analytics, real-time data processing, and more effective decision-making processes. AI-driven analytics can predict potential injuries, optimize training regimens, and provide real-time feedback to athletes, thus enhancing performance and reducing injury risks (Ǵamez Ḿıaz et al., 2020). Integrating AI with DTs can also support strategic planning by simulating various competition scenarios and providing data-driven recommendations to coaches and athletes (Douglass et al., 2024).

AI technologies can automate complex data analysis and pattern recognition tasks, allowing human experts to focus on higher-level strategic decisions. For example, AI can analyze video footage to tag events and assess player performance automatically, which is invaluable for coaches and analysts aiming to develop effective training and game strategies (Naughton et al., 2024).

Additionally, the implementation of virtual coaching through DTs is an emerging field. AI-driven virtual coaches can offer personalized training programs, monitor progress, and adjust training plans in real-time. These virtual coaches can simulate human coaching interactions, providing motivation and support to athletes, thus enhancing the training experience (Fister et al., 2019). The AST concept is a prime example of integrating AI with DTs for virtual coaching. The AST can plan, monitor, and evaluate training sessions, providing detailed feedback and adjustments based on real-time data. It can also recommend nutritional plans, and help prevent overtraining by analyzing performance indicators (Fister et al., 2019).

Another important domain is Advanced Data Analytics, which can provide deeper insights into athletic performance, injury prevention, and recovery processes. By leveraging big data and sophisticated analytical tools, DTs can analyze vast data to identify patterns and trends, offering actionable insights to optimize training and performance (Barricelli et al., 2020). For instance, AI systems can analyze the spatiotemporal behavior of athletes, such as soccer players, to identify dynamic attack formations, which can be valuable for tactical training (Cossich et al., 2023).

The advancement of sensor technologies will enhance the accuracy and reliability of data collected by DTs. Innovations in sensors can lead to better monitoring of physical and environmental conditions, enabling more precise and comprehensive digital representations (R. Ǵamez Ḿıaz, 2021). Advanced sensors, such as 3D accelerometers and bio-sensors, can capture detailed data about an athlete's movements and physiological state, which is crucial for creating accurate digital twins that reflect real-world scenarios (Douglass et al., 2024). These sensors allow for continuous monitoring, and provide real-time data that can be used to make immediate adjustments in training and performance strategies (Naughton et al., 2024).

DTs also offer a powerful tool to counteract the negative effects of a sedentary lifestyle. By creating personalized fitness programs, DTs can help individuals engage in regular physical activity tailored to their needs and con– ditions. These programs can be designed to fit into busy schedules, providing real-time feedback and adjustments to ensure the most effective exercise routines. For instance, a DT can monitor daily activity levels and suggest exercises that can be done at your desk or during short breaks, promoting a more active lifestyle (Ǵamez Ḿıaz et al., 2020; Laamarti, 2019).

In addition to enhancing general well-being, DTs play a crucial role in supporting amateur sports. Many amateur athletes lack access to professional coaching due to financial or geographical constraints. DTs can bridge this gap by providing the guidance and expertise typically offered by real coaches. Systems like the AST, supported by DTs such as the AST Monitor, can simulate the role of a coach, offering tailored training advice and feedback (Fister et al., 2021). By leveraging AI and advanced data analytics, these systems can provide real-time, personalized coaching and performance optimization, making high-quality training accessible to a broader audience (Sperlich et al., 2023).

Practical implementations of DTs in sports extend beyond virtual coaching and data analysis. Drones and other autonomous devices can be integrated with DT systems, to monitor and analyze sports activities from different perspectives. For example, drones with advanced sensors and cameras can capture aerial footage and real-time data from training sessions, providing a comprehensive view of an athlete's performance and environmental conditions. This integration allows for enhanced tactical analysis and strategic planning (Fister et al., 2019).

The future development of DTs in sports offers numerous opportunities for advancing sports analytics, personalized coaching, and strategic planning. By integrating advanced technologies, enhancing data analytics, improving sensor technologies, and ensuring ethical data management, DTs can enhance athletes' and coaches' training, performance, and overall experience significantly. These advancements are poised to make DTs an integral part of sports, driving innovation and excellence in athletic performance and management (Ǵamez Ḿıaz, 2021; Douglass et al., 2024).

9. Conclusion

This paper reviewed the role and impact of DTs in sports. Our review began by discussing the general concept of DTs. Using the SLR, we analyzed a collection of papers, to understand the current state of research and real-world applications of DTs. Four research questions were set in the beginning of the paper that are complete, as follows:

*9.1. **RQ1**: Which sports are supported the most by DTs?*

Our SLR revealed that individual sports, particularly **cycling**, **fitness**, and **football**, have seen the most significant support from DT technology. Other sports, like shooting, dancing, swimming, and gymnastics, have also seen the application of DTs, although to a lesser extent. Additionally, DTs have been applied in education, particularly physical education, providing valuable insights and enhancing the learning experience (see Section 5).

*9.2. **RQ2**: What is the level of maturity and practical implementation of DT technology in sports settings?*

The maturity and practical implementation of DT technology in sports are varied. Some DT systems, such as **AST Monitor** and **DTCoach**, are relatively mature and documented across multiple studies, indicating a higher level of development and application readiness. These systems demonstrate robust real-world applications with practical training and performance analysis benefits. However, many DT implementations are still in the prototype or experimental stages, with ongoing research needed to enhance their scalability, efficiency, and integration into everyday sports settings. This suggests that, while DT technology holds significant promise, widespread adoption and standardization are still in progress (see Section 6).

Our proposed taxonomy classifies DTs in sports according to their types, applications, and traits, providing a structured framework that can guide future research and development. This taxonomy helps to clarify the diverse roles that DTs can play in different sports disciplines and training scenarios (see Section 5).

*9.3. **RQ3**: How do DTs influence sports training?*

DTs enhance sports training significantly by providing detailed, real-time feedback, **personalized training programs**, and advanced **performance analysis.** Integrating data from sensors and wearable devices allows DTs to offer insights into an athlete's biomechanics, physiological responses, and overall performance. This allows for training interventions, rapid adjustments during training sessions, and more informed decision-making by coaches and athletes. For example, DTs can simulate various training scenarios, optimize techniques, and **prevent injuries** through detailed analysis. Using DTs in **strategic planning and competition simulation** further help refine tactics and improve overall performance outcomes (see Section 7).

*9.4. **RQ4**: What are the challenges of implementing DTs in sports?*

Implementing DT technology in sports presents several challenges. **Technical and setup challenges** include the need for standardized data acquisition methods, interoperability of different sensor technologies, and userfriendly interfaces. Ensuring the reliability and accuracy of data captured by various sensors is crucial for the effective functioning of DT systems. **Expertise requirements** pose another significant challenge, as the development and operation of DTs require multidisciplinary collaboration and specialized knowledge. **Data security and privacy** are also critical concerns, given the sensitive nature of the data involved in DT applications. Ensuring compliance with data protection regulations and maintaining ethical data management practices are essential for adopting DT technology in sports successfully (see Section 8).

Looking forward, the future development of DTs in sports presents numerous opportunities. Integrating advanced technologies such as artificial intelligence and machine learning can further enhance the capabilities of DTs. Improved data analytics and advancements in sensor technology will lead to more accurate and reliable digital models. These developments promise to refine the effectiveness of DTs, making them an integral part of sports training and performance optimization.

In summary, while the adoption of DTs in sports is still in its early stages, their potential to revolutionize the industry is immense. As technology evolves, DTs are poised to become a critical tool for athletes and coaches, driving advancements in training, performance monitoring, and strategic planning. It is important for DTs to be adopted in various sports, and to advance beyond the prototype stage into fully integrated systems. The ongoing research and innovation in this field will undoubtedly shape the future of sports, making it an exciting area for further exploration and development.

CRediT authorship contribution statement

Tilen Hliš: Conceptualization, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Iztok Fister:** Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Iztok Fister Jr.:** Conceptualization, Methodology, Supervision, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Tilen Hliš reports financial support was provided by Slovenian Research Agency. We want to declare that our co-author Iztok Fister Jr. is the associate editor of Expert Systems with Applications journal. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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