Journal of Coaching and Sports Science
Volume 4, Issue 2, 101-117.
e_ISSN: 2963-1483
https://www.journal.foundae.com/index.php/jcss/index
DOI: 10.58524/jcss.v4i2.717

The Role of Big Data Analytics (BDA) in Sport: Sports Data Mining

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Article Info

Article history:
Received: April 26, 2025
Revised: September 4, 2025
Accepted: October 25, 2025

Keywords:
Big data analysis;
Sports coaching;
Sports technology;
Performance analysis.

Abstract

Background: Big Data Analytics (BDA) is urgently needed in Indonesian sports to improve evidence-based decision-making, athlete development, and organizational management. While BDA has transformed global sports through data-driven insights, its application in Indonesia remains limited and fragmented. The absence of integrated analytics between athlete performance and organizational quality management hinders the creation of sustainable, long-term development systems. **Aims:** This study investigates how BDA can enhance athlete development and organizational management by analyzing multidimensional data from athletes, coaches, referees, and sports infrastructures. It also aims to identify dominant predictors of athlete performance across various sports and to evaluate the quality management practices of the National Sports Committee of Indonesia (NSCI). **Methods:** A mixed-methods sequential explanatory design was applied. The quantitative phase involved 67 athletes from six sports: football, table tennis, weightlifting, pencak silat, basketball, and karate at the Sport Training Center. Data on anthropometry, fitness, and achievements were analyzed using descriptive statistics, ANOVA, Chi-Square, and regression tests. The qualitative phase involved interviews and observations with 8–12 stakeholders, while organizational quality was assessed using the Wilcoxon Signed Rank test. **Result:** Results revealed significant performance differences among sports ($F = 4.927$, $p = 0.001$). Each sport had unique dominant predictors: VO_2 max and anthropometry (soccer), agility (table tennis), muscle strength (weightlifting), endurance and height (basketball), and speed (karate). NSCI's organizational analysis showed substantial deficiencies in management, facilities, and procedures ($p < 0.001$). **Conclusion**: This study confirms that BDA is crucial in advancing sustainable sports development. By identifying sport-specific performance predictors and systemic weaknesses, BDA provides a scientific foundation for designing targeted training, improving organizational quality, and building adaptive, data-driven sports ecosystems in Indonesia. The findings highlight the urgent need for national sports bodies to institutionalize BDA as part of long-term strategic planning.

To cite this article: Soedjatmiko., Nurcahyani, A., B Satman, P., Mahud., & Nasrullah, A. (2025). The role of Big Data Analytics (BDA) in sport: Sports data mining. *Journal of Coaching and Sports Science, 4*(2), 101-117. https://doi.org/10.58524/jcss.v4i2.717

INTRODUCTION

Development of athletes over the long term is a key element of the global sports policy framework supported by various organizations (Sawiuk & Groom, 2019; Watanabe et al., 2021). Research suggests that it takes between 8 and 12 years of training or around 10,000 hours of practice for a talented athlete to reach the elite level (Hatungimana & Oladipo, 2023). According to the WHO, approximately 31.3% of adults globally and 81% of adolescents do not meet the recommended physical activity guidelines (World Health Organization, 2024). Furthermore, UNESCO reports that only 58% of countries mandate physical education for girls, and 49% of girls stop exercising during adolescence (UNESCO, 2024). During this time, various challenges can arise, such as coach turnover,

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management changes, infrastructure limitations, or even turnover of the athletes themselves due to age, injury, or achievement stagnation (Aziz et al., 2023; Rismanto et al., 2024; Varghese et al., 2022). Therefore, performance sports coaching must be designed sustainably to maintain the athlete development process despite internal and external changes.

Technological advances, especially through big data analysis, offer strategic solutions in supporting the sustainability of athlete coaching. Big data allows large amounts of data to be processed more quickly and efficiently than traditional methods (Arif et al., 2025; Pennington, 2025; P. Georgiou, 2025; Sharma & Gera, 2025). In sports training, big data is important for maintaining consistency in long-term athlete training despite changes in training organizations, coaches, or unexpected situations (Cetindamar et al., 2022). This sustainability can be achieved through consistency and commitment from all members of the organization and by utilizing accurate, structured, and easily processed sports data. This approach reflects the evidence-based management paradigm in sports science (Dubey et al., 2018). In line with the study De Silva et al., (2018), professional soccer clubs and academies widely use the Global Positioning System (GPS) to provide insight into the demands of activities during training and competitive matches.

Big sports data includes collecting, storing, presenting, and securing sports data (Cetindamar et al., 2022). This data is obtained from various sources, such as athletes, coaches, referees/judges, organizational staff, and infrastructure (Dubey et al., 2018). Data is collected through surveys, observations, interviews, questionnaires, tests, and measurements. Big data analysis allows for more measurable, structured, and sustainable coaching (Goes et al., 2021). Measurable coaching can only be achieved if every data collected from athletes is fed into a big data analysis system that supports (Sun & Li, 2021). Structured coaching requires professionally conducted long-term development, where each staff member performs their duties consistently (Pamungkas et al., 2022; Purnomo et al., 2023).

Meanwhile, continuous coaching requires long-term goals that remain in place despite personnel changes or circumstances. Thus, implementing BDA is one solution to this problem (Syahputra et al., 2023). It is a lengthy process involving many parties and complex methods (Kelly & Williams, 2020). Long-term athlete development requires complete data collection from all parties involved, including athletes, coaches, referees/judges, organizational staff, and infrastructure. This data not only needs to be kept as an archive but also needs to be quickly and accurately accessible whenever needed. For this reason, sustainable sports coaching aims to optimize performance through long-term training, from the junior level to the elite level (Custodio et al., 2024; Haniyyah et al., 2025; Zulnadila et al., 2025). In addition, sustainability also includes managing infrastructure and human resources to support the coaching process optimally (Proskurin & Stadnichenko, 2023).

However, several important issues must be addressed in supporting the sustainability of athlete coaching through big data (Assuncaõ & Pelechrinis, 2018). Among them is how to maintain the sustainability of long-term athlete development so that it remains consistent and the data collection process is carried out efficiently. In addition, sports data can be stored neatly and securely, and the data can be presented quickly and accurately. In addition, it is important to understand the function of sports data as the main guide in long-term athlete development (Morgulev et al., 2018; Soedjatmiko & Wahadi, 2020). By addressing these challenges, big data analysis is expected to become a strategic tool to support the sustainability of sports coaching and optimize performance.

Although several studies have investigated the application of BDA in assessing athletic performance, preventing injuries, and conducting tactical analysis, incorporating BDA into the overarching context of sustainable sports coaching is notably underexamined. Current literature has primarily focused on short-term performance metrics, frequently neglecting the role of BDA in enhancing long-term strategic planning, resource optimization, and sustainable decision-making in sports (Assunção & Pelechrinis, 2019; A. Liu et al., 2023; Vassakis et al., 2018). This gap is especially significant when sustainability has become a primary focus in sports management and policy. Notwithstanding the substantial increase in data accessibility and analytical instruments, limited empirical research has methodically connected big data analytics approaches to sustainability metrics, such as energy efficiency, athlete health, lifespan, or infrastructural resource management. Moreover, previous studies lack precision in delineating the integration of BDA into long-term coaching cycles, institutional initiatives, or national sports development frameworks.

Therefore, this study aims to examine the role of BDA in supporting athlete development and organizational management by analyzing multidimensional data from athletes, coaches, referees, organizational staff, and sport infrastructures. This study offers a new perspective by framing BDA as a strategic driver of sustainability in sports, moving beyond performance analysis into a broader systems-oriented view. This study also addresses critical implementation challenges often overlooked in existing research, such as disparities in data infrastructure across regions, the ethical management of athlete data, and the digital readiness of coaching institutions (Martínez-Peláez et al., 2023; Morgulev et al., 2018; Sikka et al., 2019). By identifying and analyzing these obstacles, this study provides actionable insights for stakeholders such as coaches, team managers, federations, and policymakers who wish to implement data-driven strategies for the long-term sustainable development of sports.

METHOD

Research Design

This study used a mixed methods approach with a sequential explanatory design (Vebrianto et al., 2020), in which the quantitative stage was conducted first to identify general patterns of BDA use in the context of sports, followed by a qualitative stage to deepen understanding of the quantitative findings. This approach enables researchers to combine the advantages of quantitative data derived from big data with an in-depth understanding of qualitative data.

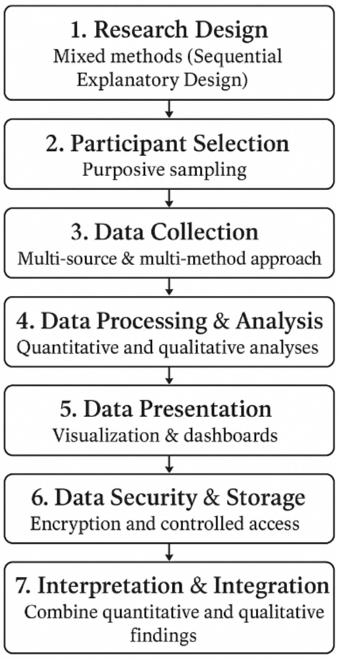

Figure 1. Sports Data through Big Data Analysis

Participants

The target population in this study was athletes from the Student Sports Education and Training Center and sports organizations that are members of INSC. Data was obtained from various parties contributing to the coaching process, including athletes, coaches, referees/judges, organizational staff, and infrastructure data supporting the training program. Sampling was conducted using purposive sampling techniques, resulting in 67 athletes aged 18-25 from six sports: soccer, table tennis, weightlifting, pencak silat, basketball, and karate. The following six sports disciplines can be selected to represent various data-generated types. Team sports (such as soccer or basketball) generate data on team strategy and interaction.

In contrast, individual sports (such as running or swimming) focus on personal and physiological performance data. Organizational data: 30+ INSC member sports administrators (based on distribution in management & quality management data). Furthermore, qualitative data were obtained from 8–12 sources: coaches, INSC administrators, sports data analysts, and scientific reviewers.

Table 1. Categories of Participants in the Study

Category	Description / Source	Number of Participants	Sports Disciplines / Focus
Athletes	Student-athletes from the Student Sports Education and Training Center	67	Soccer, Table Tennis, Weightlifting, Pencak Silat, Basketball, Karate
Coaches	Trainers involved in athlete development within INSC programs	8–12 (included in qualitative sources)	Various sports; focus on training strategies and athlete monitoring
Referees / Judges	Officials responsible for competition assessment and rule enforcement	Included among qualitative sources	Sports event officiating and technical evaluation
Organizational Staff / Administrators	INSC member sports administrators involved in management and quality control	30+	Management, policy, and organizational quality management data
Sports Data Analysts & Scientific Reviewers	Experts contributing to data analysis and evaluation of training systems	Part of qualitative data sources	Data management, analytics, and evaluation of sports performance and program effectiveness
Infrastructure Data	Records of facilities, equipment, and resources supporting the training program	—	Supporting data for training environments and logistics

Tests and Measurements

Test and measurement instruments assess athletes' physical fitness profiles and performance capacities. The tests used refer to the Physical Ability Test Battery developed and adapted from the standard guidelines of the Indonesian National Sports Committee (KONI, 2022). These tests evaluate various components of basic physical abilities such as speed, endurance, flexibility, coordination, and strength. The main purpose of using these instruments is to obtain an overview of the athletes' initial abilities and to monitor their progress during the training program. The test consists of five main components: a 40 m sprint for speed, a sit-up test for core muscle endurance, a sit-and-reach test for flexibility, a standing broad jump for explosive strength, and a shuttle run for agility. Each test result is assessed based on standardized performance norms and converted into excellent, good, fair, poor, and very poor categories. Three sports science experts have confirmed the content validity of this instrument, while its reliability shows a Cronbach's α coefficient of 0.87 based on previous test results.

Procedure

Data collection procedures were carried out through surveys, observations, interviews, and questionnaires, as well as tests and physical measurements conducted in four main stages. The first stage is the collection of data from various sources, including athletes, coaches, referees/judges, organizational staff, and infrastructure data that supports sports activities. The second stage is the processing and analysis of data using quantitative and qualitative techniques in accordance with the type of instrument used. The third stage is the rapid and accurate presentation of data in various formats, such as tables, dashboards, and video analysis, that enable comprehensive evaluation of athletes' performance and techniques. The fourth stage is the implementation of data security measures to ensure data integrity and confidentiality, with a storage system that allows authorized parties easy access while remaining protected from unauthorized access.

The data collected includes demographic information on athletes, health test results, anthropometric data, physical abilities, and competition performance results. In addition, video recordings of training sessions and matches are also used to analyze athletes' techniques and strategies. We also document data related to coaches, referees, organization administrators, and supporting facilities to ensure the effectiveness of coaching and the utilization of sports infrastructure. This comprehensive data collection enables coaches and support teams to design data-driven training programs, conduct objective athlete selection, and predict future performance based on systematically monitored development trends.

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Surveys and Questionnaires

Surveys and questionnaires are used to obtain quantitative data on respondents' perceptions and attitudes toward applying data analytics in sports coaching processes. These instruments are designed to measure three main constructs: perceptions of the usefulness of data analytics, organizational support, and training consistency. The measurement scale is a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The questionnaire items were adapted from verified instruments used in sports management research (Dubey et al., 2019). The reliability test results showed a Cronbach's α value of 0.89, indicating this instrument's high level of internal consistency.

Interviews

Semi-structured interviews were used to gain deeper qualitative insights into training effectiveness, data utilization, and the sustainability of athlete development programs. Semi-structured interviews allowed researchers to explore participants' answers in greater depth. A total of 12 informants participated in these interviews: coaches, sports administrators, sports data analysts, and referees/judges. The interviews aimed to elucidate their perceptions regarding the implementation of data-driven coaching systems, the challenges encountered during this process, and the significance of big data analytics in the long-term monitoring of athletes. The entire interview process was recorded in audio format and transcribed verbatim.

Observations

Observations were conducted to document athletes' behavior during training, technique execution, and interactions between coaches and athletes. The main focus of the observations was on the execution of movement techniques, communication during training, adherence to training plans, and the use of supporting technologies such as video analysis and GPS tracking. Observation data is recorded in the form of field notes and video documentation, then analyzed descriptively to identify performance patterns and consistency of behavior during training. One focus of observation is "the frequency of direct feedback given by coaches during training sessions."

Data Analysis

This process begins with data collection and cleaning to ensure the accuracy of the information. Descriptive statistics are used to describe the main characteristics of the data. At the same time, inferential analysis tests the relationships and differences between variables, such as the effect of physical tests on athlete performance. Data visualization, through tables, dashboards, and video analysis, can help understand the patterns that emerge from the analysis, and the final results are used to make data-driven decisions in designing training programs, evaluating performance, and managing resources more effectively in athlete development. Data analysis was assisted using SPSS 26 applications.

RESULTS AND DISCUSSION

Results

Interviews with coaches, data analysts, and organizational administrators revealed that most sports organizations still rely on manual or semi-digital systems to record athlete data. Data from physical tests, anthropometry, and match performance are often stored separately, making long-term tracking difficult.

"We have data on athletes' test results, but they're in Excel sheets that are never connected to the competition data," explained one coach.

"Each department has its own files. There's no unified system that allows us to see the athlete's full progress," added an administrator from the INSC.

This disjointed methodology results in inefficiencies and information loss, particularly during management or coaching personnel transitions. The absence of integration hinders predictive analytics, a primary benefit of Big Data systems in sports (Dubey et al., 2019).

Coaches emphasized that data analysis helps design individualized training programs tailored to athletes' physiological and psychological profiles. However, the implementation of analytics-based decision-making is still limited.

"If we could analyze weekly data trends, we could detect fatigue earlier and prevent injury," said a strength coach from the weightlifting program.

A pencak silat coach mentioned, "We rely on observation rather than metrics, so sometimes the training load isn't accurate. "

These insights indicate that coaches recognize the potential of Big Data but lack the tools or technical capacity to apply it consistently. Watanabe et al., (2021) report similar findings, arguing that consistent data utilization, as opposed to sporadic use, is crucial for sustainability in sports training.

The distribution of physical ability categories shows striking differences between sports. In soccer, categories vary greatly, with 35.3% of athletes in the Very Poor category and only 5.9% reaching Very Good. Table tennis shows fluctuations, with most athletes in the Good (37.5%) and Fair (37.5%) categories, but there are injured athletes in the Very Poor category (12.5%). Weightlifting shows relatively good physical performance, with 30% of athletes in the Very Good category and 40% in Fair. In contrast, basketball showed significant weaknesses with 58.3% of athletes in the Poor category and none reaching the Good or Very Good categories. Pencak silat had a more balanced distribution with 54.6% of athletes in the Good and Very Good categories. Karate recorded the most outstanding results, with 66.6% of athletes in the Good–Very Good category and none in the low category. The physical test results show that karate, pencak silat, and weightlifting excel, while basketball and soccer face major challenges in terms of basic physical aspects. The results can be seen in Table 2.

Table 2. Athletes' Physical Performance Test Results

Soccer				
Category	**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Very Good	1	5.9	5.9	100
Good	6	35.3	35.3	94.1
Fair	3	17.6	17.6	58.8
Poor	1	5.9	5.9	41.2
Very Poor	6	35.3	35.3	35.3
Total	17	100	100	
Table Tennis				
Category	**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Very Good	0	0	0	0
Good	3	37.5	37.5	37.5
Fair	3	37.5	37.5	75
Poor	1	12.5	12.5	87.5
Very Poor	1 (injury)	12.5	12.5	100
Total	8	100	100	
Weight Lifting				
Category	**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Very Good	3	30	30	30

Good	1	10	10	40
Fair	4	40	40	80
Poor	2	20	20	100
Very Poor	0	0	0	0
Total	10	100	100	
		Basketball		
Category	**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Very Good	0	0	0	0
Good	0	0	0	0
Fair	5	41.7	41.7	41.7
Poor	7	58.3	58.3	100
Very Poor	0	0	0	100
Total	9	100	100	
		Pencak Silat		
Category	**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Very Good	2	18.2	18.2	18.2
Good	4	36.4	36.4	54.6
Fair	4	36.4	36.4	90.9
Poor	1	9.1	9.1	100
Very Poor	0	0	0	100
Total	11	100	100	
		Karate		
Category	**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Very Good	2	22.2	22.2	22.2
Good	4	44.4	44.4	66.7
Fair	3	33.3	33.3	100
Poor	0	0	0	100
Very Poor	0	0	0	100
Total	9	100	100	

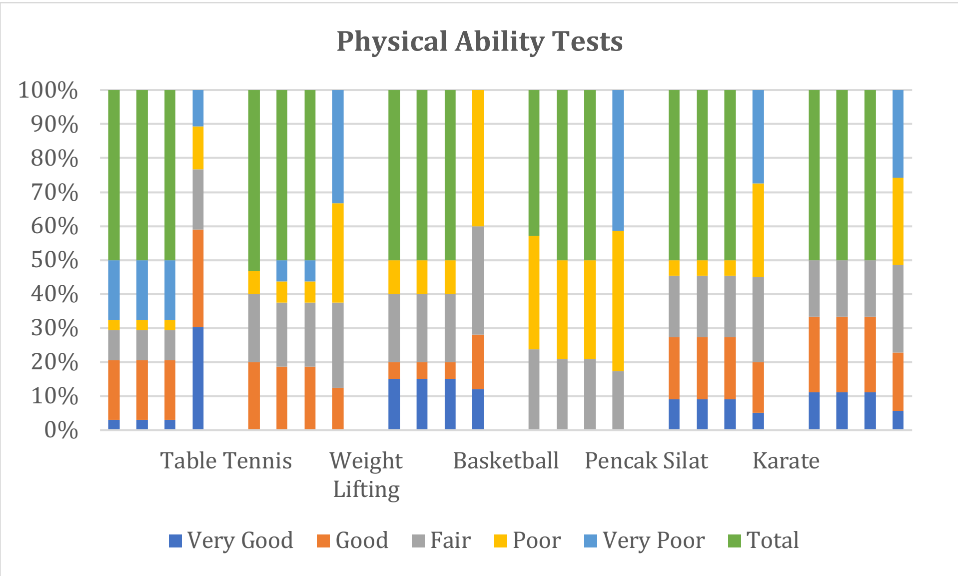

Figure 2. Diagram of SSETC Athletes' Physical Ability Test Results

Distinct performance trends were identified across sports based on the descriptive analysis results in Table 3. Karate exhibited the highest average performance, succeeded by pencak silat, reflecting athletes' significant superiority in these disciplines. Conversely, basketball demonstrated the lowest average performance, whereas table tennis displayed comparably modest outcomes. The ANOVA results show substantial differences between sports categories ($p < 0.05$), indicating that the type of sport substantially affects performance results. The results can be seen in Table 4.

Table 3. Descriptive Results of Athletes' Achievements by Sport

Sports	N	Minimum (Category)	Maximum (Category)	Mean (Score*)	Std. Deviation	General Information
Soccer	17	1 = Very poor	5 = Very Good	2.76	1.26	Majority Fair–Good, 41.2% low category
Table Tennis	8	1 = Very poor	4 = Good	2.50	1.07	Fluctuating, some athletes injured (Very Poor)
Weightlifting	10	2 = Poor	5 = Very Good	3.60	1.07	Fairly strong, 30% Excellent category
Pencak Silat	11	2 = Poor	5 = Very Good	3.64	0.92	Consistent, >50% Good–Excellent
Basketball	12	2 = Poor	3 = Fair/Average	2.42	0.51	Low, majority Poor (58.3%)
Karate	9	3 = Fair	5 = Very Good	3.89	0.78	Highest, 66.6% Good–Very Good

The average scores show karate as the sport with the highest performance (M = 3.89), followed by pencak silat (M = 3.64) and weightlifting (M = 3.60). Soccer and table tennis are in the middle (M = 2.70 and 2.50), while basketball has the lowest average score (M = 2.42). There is a clear performance hierarchy among sports, with karate, pencak silat, and weightlifting excelling, while basketball is the weakest. The results can be seen in Table 4.

Table 4. Average Natural Achievement between Sports

Sports	N	Average Achievement (1–5)	Std. Dev.
Soccer	17	2.70	1.21
Table Tennis	8	2.50	1.07
Weightlifting	10	3.60	1.07
Pencak Silat	11	3.64	0.92
Basketball	12	2.42	0.51
Karate	9	3.89	0.78
Total	67	3.12	1.11

The ANOVA test findings in Table 5 indicate substantial variations in average performance among sports (F = 4.927; p = 0.001) with a p-value less than 0.05. This verifies that performance variances are both descriptive and statistically substantiated. Consequently, over 29% of the diversity in athletic performance can be attributed to disparities among sports disciplines. The findings indicate that the sport type significantly affects athletes' performance outcomes.

Table 5. ANOVA Test Results

Source	SS	df	MS	F	Sig.
Between Groups	16.842	5	3.368	4.927	0.001*
Within Groups	41.024	61	0.672		
Total	57.866	66			

The Chi-Square test shows a significant difference in the distribution of achievement categories between sports (χ^2 = 42.351; df = 20; p = 0.002). These results align with the ANOVA findings, reinforcing that the characteristics of the sport greatly influence the distribution pattern of achievements. The distribution of achievement categories is not uniform, indicating fundamental differences in athlete quality based on sport. The results can be seen in Table 6.

Table 6. Chi-Square Tests

Test	Value	df	Sig. (2-sided)
Pearson Chi-Square	42.351	20	0.002*
Likelihood Ratio	39.874	20	0.004
N of Valid Cases	67		

Linear regression analysis identified the dominant factors that influence performance in each sport. In soccer, height and VO_2 max were the main predictors (R^2 = 0.428; p = 0.012). Table tennis performance was influenced by agility (R^2 = 0.394; p = 0.041). Weightlifting is influenced by body weight and muscle strength (R^2 = 0.502; p = 0.009). Pencak silat is influenced by height and agility (R^2 = 0.468; p = 0.017). Basketball is influenced by height and endurance (R^2 = 0.559; p = 0.005). Karate is influenced by speed and VO_2 max (R^2 = 0.446; p = 0.029). The dominant physical factors differ between sports, with anthropometry being momentous in team sports, while speed and agility play a role in individual sports. The results can be seen in Table 7.

Table 7. Athletes' Performance from Anthropometry & Physical Data

Sports	Dominant Factors of Performance (Significant)	R^2	p-value
Soccer	Height, VO_2 Max	0.428	0.012*
Table Tennis	Agility	0.394	0.041*
Weightlifting	Weight, muscle strength	0.502	0.009*
Pencak Silat	Height, agility	0.468	0.017*
Basketball	Height, endurance	0.559	0.005*
Karate	Speed, VO_2 Max	0.446	0.029*

Note: significance (*) at $p < 0.05$

Interviews with sports administrators identified institutional limitations such as inadequate digital infrastructure, low digital literacy, and limited budgets for technology adoption.

"We want to implement a centralized data system, but the internet connection and devices here are still minimal," explained one official.

"Only a few staff can use advanced software like Smartabase or Sportscode," noted another respondent.

These constraints align with the quantitative data, which shows significant management and procedural gaps (Table 8). Without adequate infrastructure and staff training, the potential of Big Data Analytics remains underutilized.

The analysis of the quality of NSCI member sports organization management shows a significant gap in all domains evaluated. The Wilcoxon Signed Rank test results show a negative Z value with a significance level of $p < 0.001$ in six main aspects: personnel, management, facilities, equipment, procedures, and environment (Table 8). The results of the KONI organizational management analysis show a significant gap in all domains: personnel (Z = -7.368; $p < 0.001$), management (Z = -8.124; $p < 0.001$), facilities (Z = -7.136; $p < 0.001$), equipment (Z = -7.153; $p < 0.001$), procedures (Z = -7.132; $p < 0.001$), and environment (Z = -7.710; $p < 0.001$). These findings indicate structural and managerial weaknesses that may affect the sustainability of athlete development programs. NSCI's organizational management still faces systemic weaknesses in all aspects, requiring comprehensive improvements to support big data-based athlete development.

Table 8. Analysis of NSCI Organizational Management (n = 30+)

Domain	Z-value	Sig. (2-tailed)	Conclusion
Personil	-7.368	0.000	There is a significant gap
Management	-8.124	0.000	There is a significant gap
Facility	-7.136	0.000	There is a significant gap
Equipment	-7.153	0.000	There is a significant gap
Procedure	-7.132	0.000	There is a significant gap
Environment	-7.710	0.000	There is a significant gap.

Based on interviews, most NSCI officials acknowledged, *"Although physical, health, and performance data on athletes have been collected, its processing is still rudimentary and not yet integrated. This makes the data difficult to use for long-term planning, let alone predictive analysis. This situation is consistent with quantitative findings showing significant management, facilities, and procedures gaps. There are variations in performance between sports. Digital infrastructure is still lacking, and coaches need an integrated data system."*

Sources from among coaches and data analysts assess that BDA has great potential to support personalized training. They hope that the digital system can integrate anthropometric data, physical performance, video recordings of matches, and injury history, so that coaches can make faster and more accurate decisions. From an organizational perspective, interviews with KONI officials revealed the main challenges to be a limited number of personnel with an understanding of data technology, a lack of digital infrastructure, and resistance to change from manual to data-based work patterns. This explains why the results of the organizational management test (Table 7) show a significant gap in all aspects.

Discussion

Implication

This study examines BDA's role in promoting athlete development and organizational management by analyzing multidimensional data from athletes, coaches, referees/judges, organizational staff, and sports infrastructure. The ANOVA results show significant differences between sports categories, indicating that the type of sport substantially affects performance outcomes. These disparities indicate that each sport possesses distinct training variables, which can be examined more thoroughly using a BDA methodology. These findings also point to structural and managerial weaknesses that may affect the sustainability of athlete development programs. Previous research emphasizes the importance of multidimensional data ranging from physiology and anthropometry to techniques for identifying talent pathways (Kelly & Williams, 2020; Goes et al., 2021). However, these results expand the understanding by emphasizing that integrating these factors into the BDA system enables more accurate personalization of training programs.

By integrating multilevel data from athletes, coaches, referees, and infrastructure, sports organizations can design more targeted coaching programs, predict potential injuries or performance stagnation, and ensure coaching continuity despite personnel changes. In the context of BDA, this weakness can be overcome by developing digital infrastructure for sports data management, so that information about athletes, coaches, and facilities can be stored, processed, and accessed in real time (Cetindamar et al., 2022). This is in line with the idea of Dubey et al. (2018) that the success of BDA in sport development depends not only on the quality of data, but also on the readiness of organizations to manage data systematically. The application of BDA in sports has brought about significant changes in various aspects, ranging from teaching and training to health monitoring and game strategy (Abeza et al., 2023). This technology combines multiple advanced analytics tools to help coaches, athletes, and medical professionals gain sharper and more objective insights into athletes' performance and condition.

BDA's important role is optimizing sports teaching and training (Morgulev et al., 2018). In this field, BDA enables more in-depth monitoring of athletes' techniques and tactics. For example, one must understand players' strengths and weaknesses in teaching sports such as college basketball and provide more concrete feedback (Y. Liu, 2020). Thus, training becomes more data-driven and personalized, improving teaching effectiveness at both the academic and athletic levels. BDA also plays a role in athlete performance analysis. Computer vision and artificial intelligence (AI) technologies enable more efficient movement training and precise measurements (A. Liu et al., 2023). Machine learning-based systems that utilize video and motion sensors can identify techniques that need improvement or patterns of play that need modification (Zhong & He, 2022). These technologies are useful in professional sports and sports training for beginners or amateurs, where proper technique is essential to avoid injury and improve performance.

Moreover, BDA-assisted athlete health monitoring paves the way for more sophisticated and data-driven fitness management. One concrete example is the BD-CVM (Big Data-Assisted Computer Vision Model) model that can monitor athletes' physical condition in real-time (Jin & Zhan, 2024). The system can detect potential injuries or overexertions using data from videos and sensors, allowing medical teams and coaches to take preventive measures early. This is undoubtedly useful in preventing injuries that could harm the athletes' and the team's careers. BDA also offers excellent potential in game strategy and decision-making. In professional sports, data collected during matches can be analyzed to discover the opponent's play patterns and devise more effective strategies. Virtual Reality (VR) and Augmented Reality (AR), now supported by BDA, allow coaches and athletes to train in a more realistic and controlled simulated environment (Cossich et al., 2023). These technologies allow athletes to hone their skills without being limited by time or physical condition, allowing them to train in more immersive situations.

Regarding sports management efficiency, BDA helps in processing and managing huge and diverse data, reducing manual workload and improving decision-making accuracy (Jin & Zhan, 2024).

It can process data from multiple sources, such as match videos, sensor data, and physiological information, giving a more comprehensive picture of athletes' condition and team performance (Niu & Wang, 2021). This helps make more informed and quicker decisions in determining game tactics, managing training schedules, or monitoring athletes' health. However, while BDA provides many benefits, some challenges must be overcome. One of the main challenges is data security and privacy. Given the large amount of personal data collected, such as health and performance information of athletes, measures are needed to ensure that such data is protected from potential leakage or misuse (Assuncaõ & Pelechrinis, 2018). Furthermore, despite the rapid development of this technology, further research is needed to improve the accuracy of predictive models and address potential biases in data analysis that could affect the results obtained.

Long-term athlete development requires data collection that will be used for the benefit of coaches or other parties in monitoring the development of athlete achievement (Owen et al., 2022). Data collection methods are very diverse and must be adjusted to achieve the objectives. Using the right method can help coaches and coaching staff to make more effective data-based decisions (Rönnby et al., 2018). Below are the types of data and how they are obtained. General athlete data consists of the athlete's personal data, such as the athlete's address, which is equipped with a population identification number, physical evidence in the form of an identity card, and a family card. It can also be data on shirt sizes, shoe numbers, and health insurance. Data is obtained through direct coaches and coaching staff interviews with athletes or coaches.

Video analysis is one of the most important data sources in the training process. Recorded data taken with a specific focus on the athlete in detail will be used as an evaluation tool to correct basic technique errors made by the athlete (Ávila-Moreno et al., 2018). Video recordings can be compared between the activities performed by the athlete and the correct technique. This toolkit can be used correctly. The coach and the athlete in question need video analysis during training. Videos are made when training is in progress. Shooting is done during technique training and games training. Video analysis of the match is needed as an evaluation material for athletes when competing. Athlete deficiencies and advantages in the physical, technical, tactical, and mental form can be recorded clearly. The results of this recording also show or evaluate the opponent's physical, technical, tactical, and mental abilities. The purpose of match recording is for athlete and team evaluation materials and correcting mistakes made by them (Ahmed & Hassan, 2022).

In conclusion, BDA has brought about a major transformation in sports, providing opportunities to improve athlete performance, optimize training strategies, and monitor athlete health and fitness. While security and technology integration challenges remain, the potential offered by BDA promises to revolutionize how sports are managed and analyzed. As technology advances, BDA will become essential in defining new ways of training, playing, and managing health in sport.

In manual data storage, all data is recorded on a record sheet and then bundled according to the type of data, whether general, health, physical test results, or other data types. This data storage is related to documents stored in hard copy form that are stored in files. Manual data storage requires a large space to store the data correctly. The second drawback is that if data is needed, it takes a long time to find, considering that the more data there is, the more difficult it is to find (Elnour et al., 2022). Data can be stored on physical devices or media directly connected to the user's system, such as a computer or laptop. The data in question is in the form of files, programs, or other data. At the same time, data in videos or photos and other data with large capacities can be stored separately to make it easier when needed.

The advantage of using local data storage is that security is better maintained because it only enters one device and cannot be accessed by others via the Network. Local storage does not require an internet connection to access it. The drawback is that if there is damage to the device, all data will be lost. Centralized data storage means that data is stored in one physical location or a centralized storage system. The form is a server or data center, so management and maintenance are easier because the data is centralized. All devices that need access will be connected to the data through the application (Ávila-Moreno et al., 2018). The creation of specialized applications will be very helpful for the development of sports databases. Applications make storing and presenting data easier when needed, and policymakers can easily and quickly access and download the data they need.

These findings indicate structural and managerial weaknesses that could affect the sustainability of athlete development programs. NSCI's organizational management still faces systemic weaknesses in all aspects, requiring comprehensive improvements to support big data-based athlete development. Data presentation is organizing, visualizing, and presenting data so that the audience or user easily understands the information (Jones, 2022). The goal is to make the data easier to analyze and interpret. Data that is stored properly can also be accessed by interested parties. Decisions taken will be late if stakeholders cannot quickly access the data (Wan, 2022). The form of data presentation that is often used is a table. Tables allow data to be arranged in rows and columns. Tables are a systematic and structured way to display numerical or categorical data. Other data presentations using dashboards and video analysis effectively visualize information in a form that is easier to understand (Peachey et al., 2018).

The last data presentation is in videos and animations to present data or information, which can explain complex data or human movements in detail (Perreault & Gonzalez, 2021). Maintaining data security is very important for individuals and organizations, including those in sports. Maintaining security is essentially protecting data from unauthorized parties. Maintaining data security also guards against damage, loss, or misuse by parties who do not have the right to access data. Data security needs to be maintained to collect data. Considering that other parties, especially competitors, should not see the data. Access restrictions need to be placed on certain parties. Some parties can only see and only on certain pages. Some parties can see the whole. Some parties can see and edit existing data. Maintaining data security is an activity that requires a multi-layered approach. By implementing various protection measures ranging from encryption, backup, and access control to monitoring, we can ensure that data remains safe from threats from other parties (Kumar & Revathy, 2020).

Research Contribution

BDA is an important tool in long-term athlete development through various aspects supporting performance monitoring and improvement (Morgulev et al., 2018). First, BDA can be used to monitor athletes' performance from various aspects, such as physical conditions including strength, speed, endurance, agility, balance, and explosiveness, as well as technical aspects such as movement conformity, speed in decision making, and ability to cooperate (Assuncaõ & Pelechrinis, 2018). In addition, advanced cameras and motion tracking devices allow coaches to conduct in-depth analysis of athletes' techniques and movements, providing more precise and personalized feedback to improve training efficiency.

BDA also enables personalization of training programs, where coaches can design programs tailored to the specific needs of each athlete based on the data collected. This includes more precise adjustments to training intensity, exercise type, and recovery to achieve peak athlete performance. In addition, BDA also supports recovery monitoring and reduces the risk of injury by analyzing historical data, training patterns, and other physical information, allowing coaches and medical personnel to plan more effective recovery (Sikka et al., 2019). The application of BDA also provides benefits in predicting athlete performance in various conditions and matches, which helps coaches make decisions regarding strategy, tactics, and selection of the right athletes for a particular competition (Y. Liu, 2020). BDA also serves as a basis for determining policies and assignments, such as selecting coaches, referees, and administrative ranks based on data on qualifications and experience (Goes et al., 2021). With complete and accurate data, organizations can make more informed decisions, such as assigning referees according to their qualifications and certifications.

In addition, BDA allows comparison between athletes from other teams or even countries, which can help identify their strengths and weaknesses. This helps customize training and strategies to improve competitiveness (Rozi et al., 2023; Rubiyatno et al., 2023; Tanri et al., 2023). A more valid and data-driven athlete selection process also ensures that decisions support athletes' achievements and career development (Morgulev et al., 2018). Finally, long-term coaching sustainability is also maintained through comprehensive data, which allows new administrators and coaches to continue the program without starting from scratch, creating efficiencies in the training and athlete management process. The BDA provides a solid foundation for the continuation and development of a more sustainable and data-driven sports coaching system.

Limitations

While offering extensive insights into using Big Data Analytics (BDA) in sports, this study has significant limitations. The research primarily relies on secondary data and literature synthesis, which may insufficiently capture the practical complexities of BDA application in diverse athletic contexts. The lack of empirical validation or field experimentation restricts the generalizability of the findings, as disparities in technical infrastructure, data literacy, and resource availability among sports organizations might markedly affect outcomes. Secondly, the study inadequately examines data collection and dissemination's ethical and regulatory ramifications. Data privacy, ownership, and security concerns especially concerning sensitive athlete health and performance data necessitate more thorough scrutiny and policy-focused evaluation. The study primarily emphasizes the prospective advantages of BDA, while ignoring the technical, financial, and organizational obstacles that could impede its implementation in developing nations or amateur sports settings. The swift advancement of data technologies indicates that the models and frameworks examined in this study may soon become obsolete, underscoring the necessity for ongoing research and longitudinal analysis to maintain relevance and application in future sports data ecosystems.

Suggestions

Future research should focus on developing an integrated BDA platform across sports disciplines, applying artificial intelligence algorithms to predict performance and injury risk, exploring the relationship between BDA and the psychological and social aspects of athlete development, and evaluating the effectiveness of data-driven policies in improving sports organization performance. This research confirms that BDA is a key driver of future sports development, linking athlete performance, health, organizational management, and technological innovation within a solid sustainability framework.

CONCLUSION

This study confirms that BDA plays a strategic role in supporting the sustainability of athlete development by integrating digital technology, predictive analytics, and systematic data management. Quantitative results show significant variations in performance between sports, while regression analysis identifies specific dominant physical factors in each sport. These findings are reinforced by qualitative results that highlight the limitations of manual recording, the lack of digital infrastructure, and the need for coaches to have an integrated data system. Thus, BDA is not just an analytical tool, but an important foundation for designing training programs that are more personalized, adaptive, and long-term oriented. Furthermore, this study shows that multidisciplinary collaboration between sports science and computer science is a key prerequisite for the optimal use of BDA. Integrating statistical methods, artificial intelligence, computer vision, and real-time data visualization opens new opportunities in performance monitoring, injury prediction, and more objective technique evaluation. This collaboration benefits sports practitioners and strengthens international research networks that accelerate innovation in sport science. From a policy perspective, this research emphasizes the need to transform the governance of sports organizations towards a data-based ecosystem, including increasing human resource capacity, developing digital infrastructure, and establishing standards for the security and ethics of athlete data management. Thus, BDA can be a strategic instrument to support sports development that is not only oriented towards short-term achievements but also towards the sustainability and resilience of the national sports system.

ACKNOWLEDGMENT

The authors thank the Faculty of Sport Science, Universitas Negeri Semarang, for funding this publication's research (financial support).

AUTHOR CONTRIBUTION STATEMENT

The first author and correspondent, S was responsible for conceptualization, investigation, and manuscript preparation. AN was responsible for data acquisition, while PSB and M assisted with methodology and manuscript preparation. Finally, AN finalized the data and acquired funding.

AI DISCLOSURE STATEMENT

The author used ChatGPT during the preparation of this work to help provide information about existing literature. In addition, it can help identify areas that have not been widely researched (research gaps). After using the tool/service, the author thoroughly reviewed and edited the content as needed and takes full responsibility for the publication's content.

CONFLICTS OF INTEREST

The authors confirm the presence or absence of any potential conflicts of interest—financial, institutional, or personal—that could influence the conduct of this study, the analysis of data, the preparation of the manuscript, or its publication.

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